

# Reasoning based on symbolic and parametric knowledge bases: a survey

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**Abstract** Reasoning is fundamental to human intelligence, and critical for problem-solving, decision-making, and critical thinking. Reasoning refers to drawing new conclusions based on existing knowledge, which can support various applications like clinical diagnosis, basic education, and financial analysis. Though a good number of surveys have been proposed for reviewing reasoning-related methods, none of them has systematically investigated these methods from the viewpoint of their dependent knowledge base. Both the scenarios to which the knowledge bases are applied and their storage formats are significantly different. Hence, investigating reasoning methods from the knowledge base perspective helps us better understand the challenges and future directions. To fill this gap, this paper first classifies the knowledge base into symbolic and parametric ones. The former explicitly stores information in human-readable symbols, and the latter implicitly encodes knowledge within parameters. Then, we provide a comprehensive overview of reasoning methods using symbolic knowledge bases, parametric knowledge bases, and both of them. Finally, we identify the future direction toward enhancing reasoning capabilities to bridge the gap between human and machine intelligence.

**Keywords** Reasoning, symbolic knowledge base, parametric knowledge base, pre-trained language models, knowledge graphs

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## 1 Introduction

Reasoning refers to inferring new conclusions from existing knowledge [1], which is fundamental to human intelligence and essential for complex tasks such as problem-solving, decision-making, and critical thinking. The cognitive process of reasoning involves using evidence, arguments, and logic to draw conclusions or make judgments [2], which can provide back-end support for various real-world applications, such as clinical diagnosis [3–5], basic education [6–8], and financial analysis [9–11]. Reasoning ability is central to human intelligence, yet modern natural language processing systems still struggle to reason based on the information they are given or have already learned [12–15]. The study of reasoning is essential in fields like neurosciences [16], psychology [17], philosophy [18, 19], and computer science [20], as it helps to narrow the gap between human and machine intelligence [15]. Hence, building an artificial intelligence system capable of reasoning is both the goal of the research community and the way to improve the performance of complex applications [1].

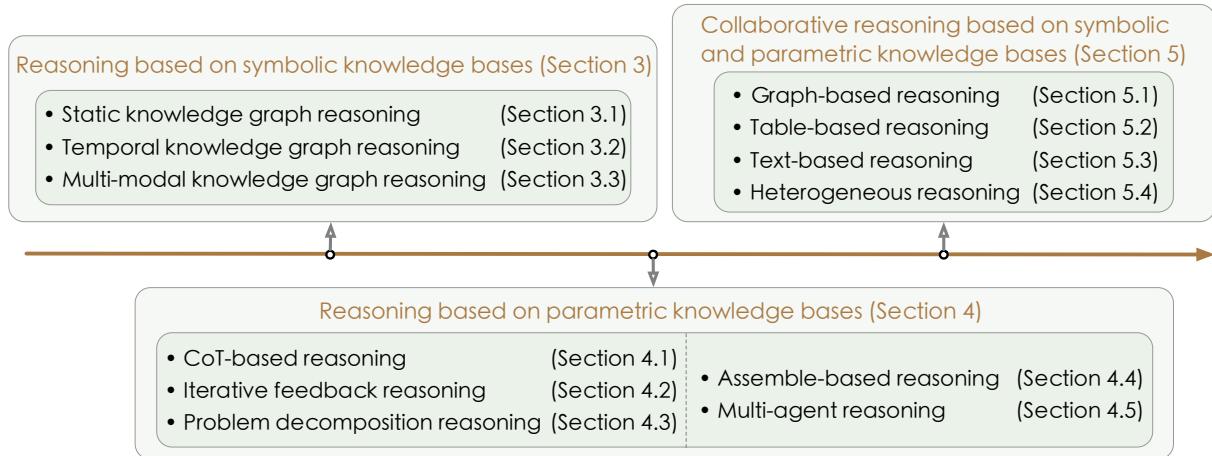
With the rapid development of reasoning technology, some surveys [1, 2, 15, 21–30] summarized the reasoning methods from different perspectives. For instance, there was a survey [1] researching reasoning using natural language format, including classical logical reasoning, natural language inference, multi-hop question answering, and commonsense reasoning. A few of them [22–25] emphasized the reasoning based on the structured facts in knowledge graphs (KGs), like temporal knowledge graph reasoning and multi-modal knowledge graph reasoning. Some studies [26–30] paid attention to the knowledge sources that the reasoning methods used for question answering, e.g., Wikidata KG and Wikipedia corpus. More recent surveys [2, 15, 21] summarized the reasoning methods by prompting large language models, such as chain-of-thought series and self-reflection series methods.

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Despite the valuable perspectives provided by these surveys, none of them has summarized reasoning methods from the view of their dependent knowledge base. As previous work [1, 2, 31] points out, reasoning is a process of integrating multiple existing knowledge to derive some new conclusions about the world, and current reasoning methods rely heavily on knowledge bases. However, both the scenarios to which the knowledge bases are applied and their storage formats are significantly different. Hence, investigating reasoning from the perspective of the knowledge base helps us gain a deeper understanding of the challenges and future directions.

In this paper, we review related work by focusing on the underlying knowledge base that supports reasoning methods. We begin by classifying these knowledge bases into two types based on their storage formats: symbolic and parametric, where symbolic knowledge bases present information in human-readable symbols like KGs and tables, and parametric ones encode information implicitly within parameters. Then, we investigate the reasoning methods based on symbolic knowledge bases, parametric knowledge bases, and both of them, respectively. Finally, we explore the challenges and potential future directions for reasoning with both symbolic and parametric knowledge. The overall framework is shown in Figure 1.



**Figure 1** Overall framework of reasoning-related methods.

In summary, the main contributions of this survey are:

- To the best of our knowledge, we are the first to provide a comprehensive survey on reasoning studies from the perspective of their dependent knowledge bases.
- We conduct a thorough investigation of various types of reasoning methods that utilize symbolic knowledge bases, parametric knowledge bases, and their combination, whereas previous reviews only focused on one of them.
- We have meticulously summarized the challenges and future research directions related to reasoning, which will contribute to advancing the development of this field.

**Organization of this survey:** we first introduce the background in Section 2. Then, we systematically introduce different reasoning tasks in Section 3, 4, 5. We discuss the challenges and future research directions in Section 6. Finally, we conclude this paper in Section 7.

## 2 Background

In this section, we first introduce the concepts of symbolic and parametric knowledge bases. In artificial intelligence, the symbolic knowledge bases and parametric knowledge bases represent different paradigms of knowledge representations that align with symbolism [32] and connectionism [33], respectively. The symbolic knowledge base involves explicit knowledge and logical structures for reasoning. It is also fundamental to symbolic AI, which focuses on rule-based manipulation of symbols [34]. In contrast, the parametric knowledge base is associated with connectionism, where neural networks capture knowledge implicitly through learned parameters, emphasizing adaptability and pattern recognition [35]. Finally, we will introduce the taxonomy of reasoning in detail.

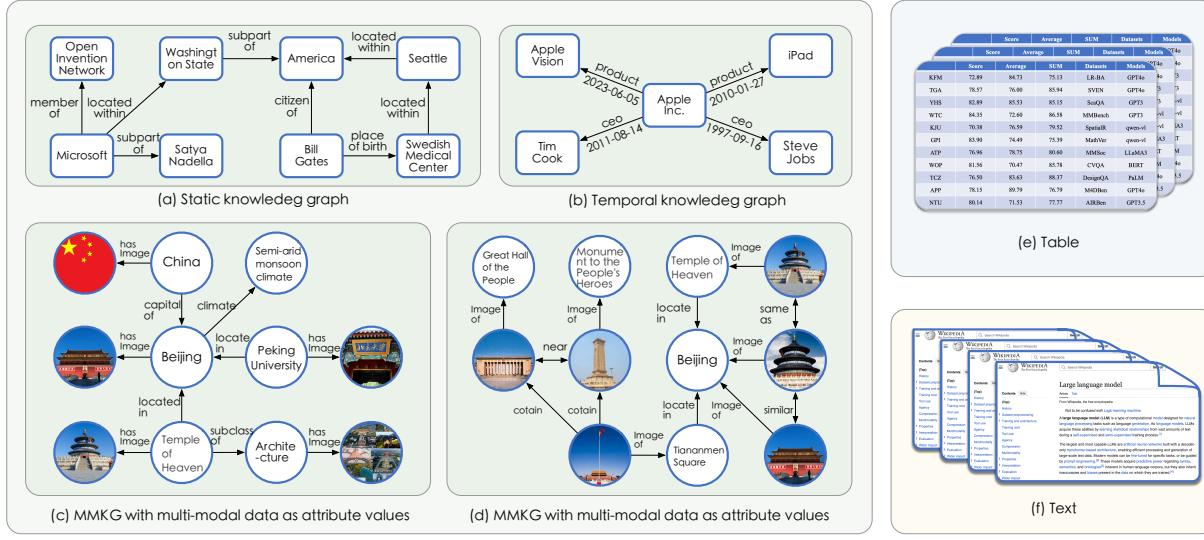


Figure 2 Different symbolic knowledge bases.

## 2.1 Symbolic knowledge bases

The symbolic knowledge bases contain KGs, tables, and text, the first two are structured and the last one is unstructured. The structured KGs can be partitioned into static knowledge graphs (SKGs), temporal knowledge graphs (TKGs), and multi-modal knowledge graphs (MMKGs). The following part of this subsection introduce the details of these symbolic knowledge bases.

**Static knowledge graph:** As shown in Figure 2 (a), an SKG is a structured semantic knowledge base that can express various associations between entities in a graphical manner [36]. An SKG contains many factual triplets  $(h, r, t)$ , where  $h$ ,  $r$ , and  $t$  represent the head entity, the relation, and the tail entity, respectively. For example,  $(\text{Microsoft}, \text{located within}, \text{Washington State})$  represents “Microsoft is located within Washington State”. An SKG is represented as  $(\mathcal{E}, \mathcal{R}, \mathcal{F})$ , where  $\mathcal{E}$ ,  $\mathcal{R}$ , and  $\mathcal{F}$  denote the entity set, the relation set, and the triplet set  $\{(h, r, t)\} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E}$ , respectively.

**Temporal knowledge graph:** As shown in Figure 2 (b), TKGs can store temporal information such as events that evolve over time. The quadruples  $(h, r, t, \text{time})$  are the basic unit of TKGs, where  $h$ ,  $r$ ,  $t$ , and  $\text{time}$  represent the head entity, the relation, the tail entity, and the timestamp, respectively. For example, the quadruple  $(\text{Apple Inc.}, \text{product}, \text{iPad}, 2010-01-27)$  means “On January 27, 2012, Apple Inc. produced iPad”. A TKG is represented as  $(\mathcal{E}, \mathcal{R}, \mathcal{T}, \mathcal{F})$ , where  $\mathcal{E}$ ,  $\mathcal{R}$ ,  $\mathcal{T}$ ,  $\mathcal{F}$  denote the entity set, relation set, the timestamp set, and the quadruple set  $\{(h, r, t, \text{time})\} \subseteq \mathcal{E} \times \mathcal{R} \times \mathcal{E} \times \mathcal{T}$ , respectively. Another representation way of TKGs is  $(G_{t1}, G_{t2}, \dots, G_{tn})$ , where  $G_{ti}$  denotes the SKG containing all triplets happened in timestamp  $t_i$ .

**Multi-modal knowledge graph:** The MMKG integrates various multi-modal data into one SKG, such as text, images, and audio. As shown in Figure 2 (c) and (d), MMKGs are generally divided into two types [36]. One represents multi-modal data as new entities, and the other one describes them as entities’ attributes.

**Structured table:** As shown in Figure 2 (e), a structured table contains  $n$  records and  $m$  attributes. Each record can be represented as a vector  $\mathbf{r}_i = (a_{i1}, a_{i2}, \dots, a_{im})$ , where  $a_{ij}$  denotes the value of the  $j$ -th attribute in the  $i$ -th record. The entire table can be viewed as a set of  $n$  records  $\{\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_n\}$ . The format of table makes data easy to store, manage, and analyze [37]. Hence, it is widely used in various fields such as financial statements, scientific research data, and inventory management [38, 39].

**Unstructured text:** As shown in Figure 2 (f), unstructured text primarily refers the text information without a standardized format or organization, such as books and articles. Unstructured text can also store knowledge and be widely used in various applications with the help of current large language models.

## 2.2 Parametric knowledge bases

Parametric knowledge bases mainly refer to pre-trained language models (PLMs). PLMs are pre-trained on large-scale text corpora via self-supervised learning and store generalized knowledge in pa-

rameters, enabling them to reason with implicit knowledge in parameters [40]. Based on architecture differences, current PLMs can be divided into encoder-only, decoder-only, and encoder-decoder.

**Encoder-only PLMs:** The representative encoder-only PLMs mainly include BERT [41] and its variants, like RoBERTa [42], ALBERT [43], DeBERTa [44], XLM [45], XLNet [46], UNILM [47], and ELECTRA [48]. Different pre-training strategies are designed to incorporate pre-training knowledge into their parameters. For instance, BERT is pre-trained through the application of mask language modeling. RoBERTa, which is built upon and optimized from BERT, makes use of dynamic masking. In terms of ELECTRA, it introduces the replaced token detection pre-training task, which enhances the learning efficiency and performance of the model. To effectively utilize parametric knowledge in encoder-only PLMs, a direct approach is extracting semantic representations from the input text. This method is widely used in reasoning tasks, such as open-domain question answering [49–52] and machine reading comprehension [53–56], to incorporate pre-trained knowledge.

**Decoder-only PLMs:** Pre-trained language models adopting the decoder-only architecture primarily focus on text generation tasks. Based on the autoregressive attribute, these models generate coherent texts by successively predicting the forthcoming content based on the already generated text. Representative decoder-only PLMs encompass GPT [57], LLaMA [58], Qwen [59], and Mistral [60]. Recently, decoder-only PLMs have demonstrated remarkable potential within the domain of text generation. Consequently, most PLMs with large parameter scales (also known as large language models, LLMs) use decoder-only architecture. During reasoning, we can elicit knowledge from LLMs through prompting methods such as chain of thought [61], iterative feedback [62], problem decomposition [63], assemble [64] and multi-agent [65]. In contrast, when using small language models (SLMs) for reasoning, it may necessary to fine-tune them using task-specific or domain-specific data to leverage the parametric knowledge contained within them effectively [66, 67].

**Encoder-decoder PLMs:** Encoder-decoder PLMs integrate both encoder and decoder components. It uses the encoder to model input text features and the decoder for text generation, with the advantage of separating vector spaces for text understanding and generation. However, it has some limitations such as high complexity and significant demands on pre-training time and computational resources. Representative encoder-decoder PLMs include T5 [68], BART [69], mBART [70], MASS [71], and ChatGLM [72]. Thanks to its structural advantages, we can utilize the encoder's semantic vector features and the decoder's target text for knowledge reasoning [73].

### 2.3 Taxonomy of reasoning

From the perspective of the dependent knowledge bases, reasoning methods can be divided into three categories: reasoning methods based on symbolic knowledge bases, reasoning methods based on parametric knowledge bases, and collaborative reasoning methods based on symbolic and parametric knowledge bases.

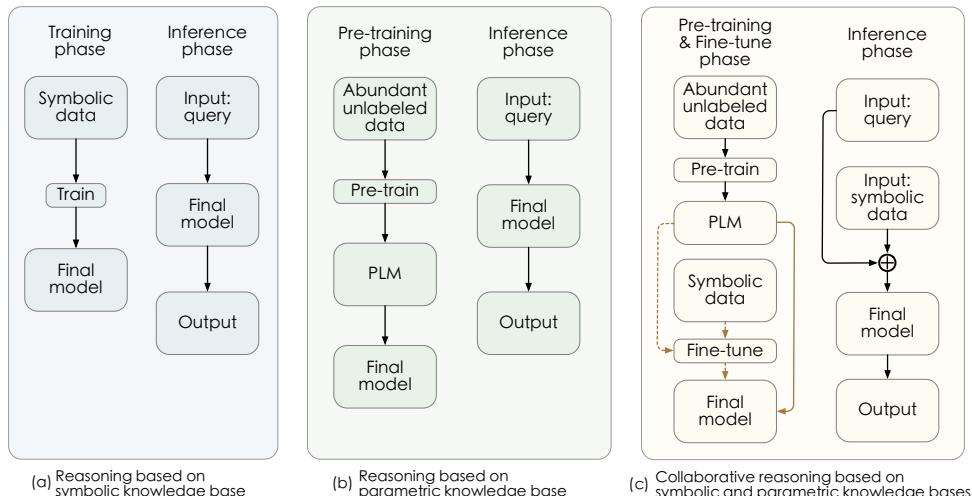


Figure 3 Different reasoning methods.

As shown in Figure 3 (a), reasoning methods based on symbolic knowledge bases train a model to learn the knowledge in the symbolic knowledge bases during the training phase. During inference, only a query is inputted to the model. The model's reasoning capability comes from the knowledge modeled in the training phase. Typical tasks for this type of method, such as static knowledge graph reasoning, require reasoning for an unknown element in an incomplete triplet or quadruple. [74, 75]

As shown in Figure 3 (b), reasoning methods based on parametric knowledge bases leverage the knowledge in PLMs' parameters. During inference, only a query is inputted. The model's reasoning capability comes from the parametric knowledge modeled during pre-training. Compared to the training phase in Figure 3 (a), the pre-training phase is usually task-independent. Typical tasks for this type of method, such as mathematical reasoning, require reasoning for a natural language answer given a knowledge-intensive question [61–63, 76, 77].

As shown in Figure 3 (c), collaborative reasoning methods based on symbolic and parametric knowledge bases also model parametric knowledge during the pre-training phase. Some methods further fine-tune the PLMs using knowledge from symbolic knowledge bases to enhance the domain knowledge learning. During inference, these methods retrieve relevant knowledge from the symbolic knowledge bases and combine it with the parametric knowledge in PLMs to enhance reasoning performance. Similar to reasoning methods based on parametric knowledge bases, this type of method, such as knowledge graph questions answering, also performs reasoning in the form of natural language question answering [78–81].

### 3 Reasoning based on symbolic knowledge base

In this section, we investigate the reasoning methods based on symbolic knowledge bases. Based on the structural types of KGs, we investigate static knowledge graph reasoning, temporal knowledge graph reasoning, and multi-modal knowledge graph reasoning. The overall taxonomy of reasoning methods based on symbolic knowledge bases is shown in Figure 4.

#### 3.1 Static knowledge graph reasoning

Static knowledge graph reasoning refers to the completion of incomplete triplets (incomplete knowledge) based on the given fact triplets (existing knowledge) in the SKG, thereby obtaining new complete factual triplets (new knowledge). According to the differences in query form and output form, static knowledge graph reasoning tasks can be divided into three sub-tasks: traditional SKG reasoning, multi-hop SKG reasoning, and SKG complex logical query answering. In general, multi-hop SKG reasoning requires providing an explicit reasoning path while completing the triplets. SKG complex logical query answering requires modeling the complex logical symbols.

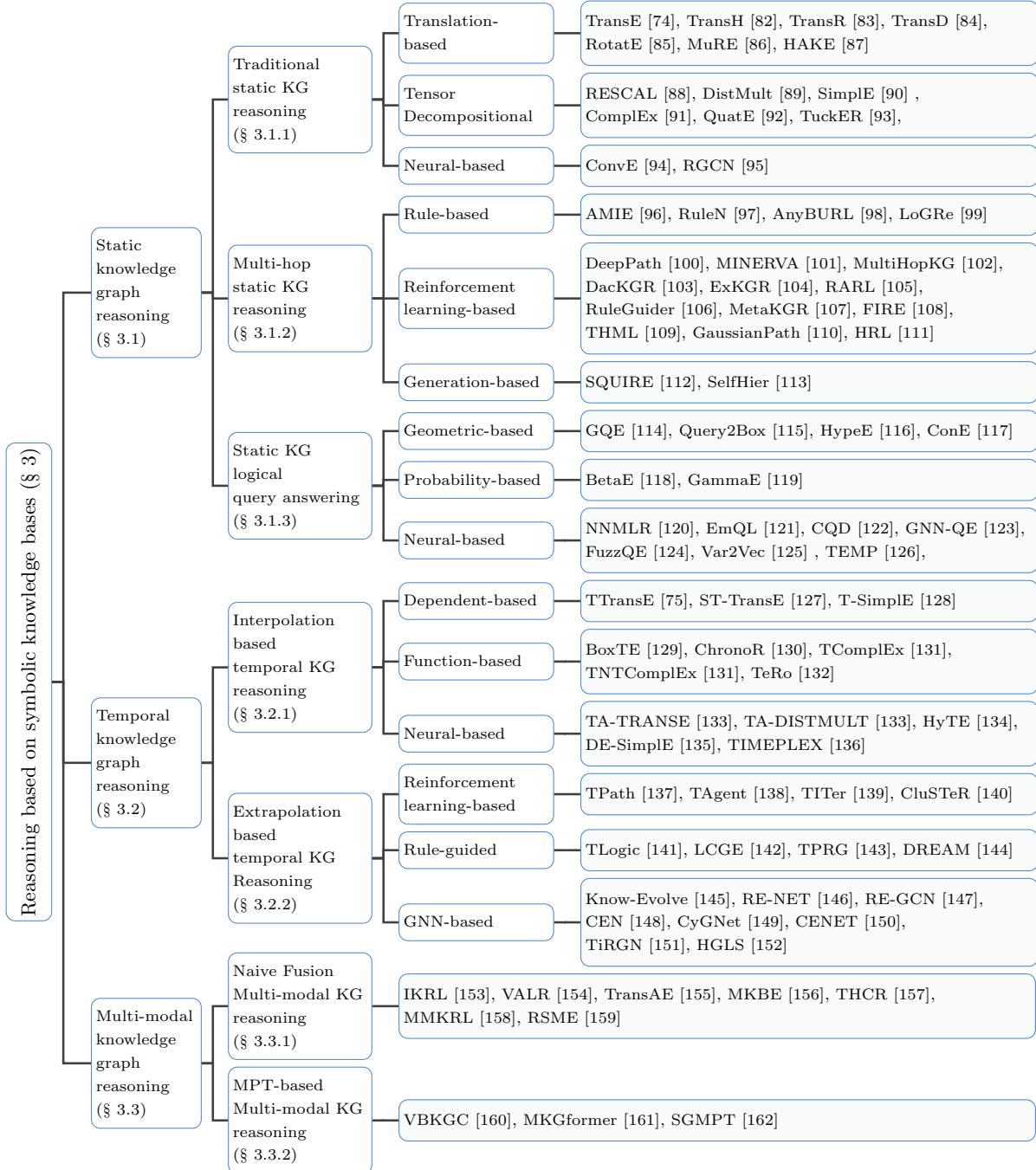
##### 3.1.1 Traditional SKG reasoning

**Task definition:** Given the query  $(h, r, ?)$ ,  $(?, r, t)$ , or  $(h, ?, t)$ , traditional SKG reasoning methods aim to predict the missing entity or relation directly. Generally, the traditional SKG reasoning methods first learn the representations of relations and entities in SKGs. Then, it constructs a scoring function to calculate the validity of possible triples. According to the representation approaches, traditional SKG reasoning methods can be categorized into three types: translation-based, tensor decompositional, and neural-based [36, 163].

###### 3.1.1.1 Translation-based methods

Translation-based methods map the entities and relations to a vector space, where entities with similar semantics are close in the distance. The role of the relation is to project the head entity representation onto the tail entity representation. A common approach is to represent relations as translation vectors from the head entity to the tail entity.

The first translation-based method TransE [74] regards the relation as a translation operation, that is,  $h + r \approx t$ , where  $h$ ,  $r$ , and  $t$  belong to the same vector feature space. However, it cannot handle certain specific relations, such as one-to-many, many-to-one, symmetric, and transitive relations. To adapt to the multiple meanings of entities and relations, TransH [82] interprets relations as transformation operations on hyperplanes, TransR [83] models different atoms in the SKG in different vector spaces with the projection matrix  $M_r$  for each relation  $r$ , and TransD [84] dynamically constructs mapping matrices for

**Figure 4** Taxonomy of reasoning methods based on symbolic knowledge base.

every entity-relation pair. Furthermore, some methods propose vector spaces that differ from traditional approaches. For example, RotatE [85] considers relation as rotation in complex space, MuRE [86] utilizes the Poincaré ball model in hyperbolic space, and HAKE [87] models semantic hierarchies based on polar coordinate space rather than relational patterns.

### 3.1.1.2 Tensor decompositional methods

Tensor decompositional methods focus on capturing the pairwise interaction between atoms in an SKG to exploit the similarity of the latent features. For example, RESCAL [88] models entities as vectors and relations as matrices to capture the interaction amounts between the elements at corresponding positions of the head and tail entity vectors. However, RESCAL is high in computational complexity and cannot model asymmetric relations. Therefore, many methods like DistMult [89], SimplE [90], ComplEx [91], QuatE [92], TuckER [93] utilize tensor decomposition to better model the semantic similarity of triples and reduce the computational complexity of the model.

### 3.1.1.3 Neural-based methods

Translation-based and tensor decompositional methods create a vector or matrix for every entity and relation, which requires large storage space for large-scale SKGs. To address the challenge, neural network methods utilize multi-layer neural networks to learn the representations of entities and relations, which avoids the storage of vectors or matrices. For example, ConvE [94] presents a simple multi-layer convolutional architecture. Inputting the head entity and relation, the encoder of ConvE calculates their deep features, and the decoder of ConvE maps them into the entity space to predict the target tail entity. Besides, since graph neural network (GNN) [164] has proven to be effective in mining the structural information of graph, it is widely applied for traditional SKG reasoning. For example, RGCN [95] encodes entities by aggregating neighbor information instead of optimizing with a single entity vector, resulting in significant performance improvements.

## 3.1.2 Multi-hop SKG reasoning

**Task definition:** Given a query  $(h, r, ?)$ , multi-hop SKG reasoning methods aim to predict the target tail entity  $t$  through a  $n$ -hop reasoning path  $\tau : h \xrightarrow{r_1} e_1 \xrightarrow{r_2} e_2 \dots \xrightarrow{r_n} e_n$ , where  $e_i$  and  $r_i$  represent the entity and the relation in the path  $\tau$ . The last entity  $e_n$  in  $\tau$  is treated as the predicted target tail entity  $t$ . Compared to traditional SKG reasoning methods, multi-hop SKG reasoning methods provide better better interpretability. The multi-hop SKG reasoning methods can be categorized into rule-based, reinforcement learning-based (RL-based), and generation-based.

### 3.1.2.1 Rule-based methods

Rule-based methods automatically induce logical rules from SKG and predict missing entities or relations by matching queries to the rules, typically without model training. The rules exist in the form of symbolic chains, such as  $mother\_of(m, c) \wedge married\_to(m, f) \Rightarrow father\_of(f, c)$ , in which some facts can be inferred from other facts. Some rule-based methods such as AMIE [96], RuleN [97], AnyBURL [98], LogRe [99] aim to efficiently mine and utilize rules in KGs. Although these methods achieve remarkable performance, they are hard to generalize in practice due to the limitation of symbolic representation.

### 3.1.2.2 Reinforcement learning-based methods

RL-based methods model the multi-hop reasoning process as a markov decision process (MDP), where the agent walks on SKG to search the target entities. DeepPath [100] first adopts the RL framework to search the reasoning paths and target relations given to the head and tail entities. MINERVA [101] proposes a more complex and practical scenario to find the target tail entities given the relations and head entities. Following MINERVA, most RL-based methods are devoted to tackling the sparse rewards problem and trying to design a more efficient policy network in incomplete SKG. For instance, Multi-HopKG [102] is one of the first to use embedding models to estimate the rewards of unobserved targets, thereby reducing the impact of incorrect negative samples. Similar methods include DacKGR [103], ExKGR [104], RARL [105], and RuleGuider [106].

Moreover, several RL-based methods have integrated meta-learning to address the decreased reasoning capability of reinforcement learning in few-shot relation scenarios. For instance, Meta-KGR [107] is the

first to apply meta-learning to multi-hop KG reasoning, using the meta-learning algorithm MAML [165] to learn meta-parameters from high-frequency relations and then quickly adapts to sparse relations. FIRE [108] uses heterogeneous neighbor information to enhance entity embeddings and leverages knowledge graph embeddings to compute structural relevance, thereby reducing the search space. THML [109] proposes a difficulty-aware meta-reinforcement learning method that trains difficulty-aware batches to predict missing elements, as well as a two-level difficulty-aware sampling strategy to effectively generate new difficulty-aware batches, greatly enhancing the generalization capability.

Recently, there have been some quite creative methods. For example, GaussianPath [110] points out that agents in traditional RL-based methods are prone to get trapped in reasoning paths. It proposes a bayesian multi-hop reasoning paradigm to capture the uncertainty of reasoning paths to explore a broader range of reasoning paths. Besides, inspired by how humans handle ambiguous situations, HRL [111] proposes a high-level policy to learn historical information and a low-level policy to recognize relation clusters. It decomposes the complex action space to express the multiple semantics of relations.

### 3.1.2.3 Generation-based methods

Generation-based methods adopt a generative framework to generate the reasoning paths step by step. For instance, SQUIRE [112] utilizes an encoder-decoder model to translate the query to a reasoning path. By leveraging the rule-enhanced and iterative training strategy, SQUIRE performs better than rule-based and RL-based methods. In cold-start multi-hop reasoning, the model always lacks precise guidance and explicit paths. To overcome these challenges, SelfHier [113] designs an effective generation-based model to explore the reasoning paths by hierarchical guidance and self-verification strategies. Overall, the generation-based methods not only obtain high performance but also has low time complexity.

## 3.1.3 SKG complex logical query answering

**Task definition:** Given an incomplete first-order logical (FOL) query, SKG complex logical query answering methods aim to predict an target entity set. For instance, the FOL query  $C_? \cdot \exists P : assoc(d_1, P) \wedge assoc(d_2, P) \wedge target(P, C_?)$  means that “identify potential drugs  $C_?$  that can act on proteins  $P$  associated with the disease  $d_1$  and  $d_2$ ”. SKG complex logical query answering methods first transform the given FOL query into a region in embedding space. Then, they output the entities within the region as the target entity set. Based on the difference of embedding space, the SKG complex logical query answering methods can be categorized into geometric-based, probability-based, and neural-based.

### 3.1.3.1 Geometric-based methods

Geometric-based methods transform queries into geometric regions with clear boundaries. The composition and transformation of queries align with the composition and transformation of their geometric regions. For example, GQE [114] proposes the geometric projection operator and the geometric intersection operator, which embeds basic query into a single point and combines basic queries into complex FOL query, respectively. Query2Box [115] effectively models query graph embeddings through hypergeometric box embeddings, where the query is represented as a box using the center and the boundary offset. All entities that fall within the box region of the query are considered the target entity set. In addition, HyPeE [116] learns representations of entities and relations as hyperboloids in a Poincaré ball. ConE [117] represents entities and queries as Cartesian products of two-dimensional cones.

### 3.1.3.2 Probability-based methods

Geometric-based methods necessitate that target entities strictly fall within the region defined by the query. However, this requirement often fails to reflect real-world scenarios where entities exhibit semantic diversity. Probability-based methods address this issue by modeling queries and entities as more flexible probability distributions. For example, BetaE [118] uses probabilistic distributions with bounded support, specifically the Beta distribution, and embeds queries/entities as distributions, which allows it to faithfully model uncertainty. Similarly, GammaE [119] utilizes Gamma distribution to capture more features of entities and queries. Based on the linear property and strong boundary support of Gamma distribution, GammaE effectively avoids generating ambiguous answers.

### 3.1.3.3 Neural-based methods

Neural-based methods model the correspondence between queries and entities using neural network. For example, NNMLR [120] uses multilayer perceptron (MLP) and MLP-Mixer to model the basic queries and their combinations. It computes the distance between the query and the entities to rank the answers. Similar methods include EmQL [121], CQD [122], GNN-QE [123], FuzzQE [124], Var2Vec [125], and TEMP [126].

## 3.2 Temporal knowledge graph reasoning

The objective of temporal knowledge graph reasoning is to leverage existing events and knowledge to reason about unseen events or predict future events. Previous research [36] primarily categorizes reasoning tasks into two scenarios: interpolation and extrapolation, depending on whether the model has seen the timestamps in the query. From a reasoning perspective, interpolation generally completes missing facts by analyzing known knowledge in TKGs, while extrapolation focuses on predicting unknown events by learning embeddings of entities and relations from historical facts on continuous TKGs.

### 3.2.1 Interpolation-based TKG reasoning

**Task definition:** Given a TKG with facts from  $time_0$  to  $time_T$ , the Interpolation-based TKG reasoning method aims to complete missing quadruple  $(h, r, ?, time_i)$  or  $(?, r, t, time_i)$  in history ( $time_0 \leqslant time_i \leqslant time_T$ ). Interpolation-based TKG reasoning methods can be divided into dependent-based, function-based, and neural-based.

#### 3.2.1.1 Dependent-based methods

Dependent-based methods generally do not involve direct manipulation of timestamps. Instead, they associate each timestamp with the relevant entity or relation, capturing the evolution of entities or relations over time. For example, TTransE [75] extends the traditional TransE [74] model by jointly encoding relations and timestamps within a unified space. Building on TTransE, ST-TransE [127] introduces a specialized time embedding method that constrains the representation learning of entities and relations. However, TTransE and ST-TransE struggle to manage evolving facts over time effectively. In contrast, T-SimplE [128] leverages a fourth-order tensor to model interactions within quadruples, improving its ability to capture temporal associations.

#### 3.2.1.2 Function-based methods

Function-based methods use specialized functions to learn embeddings for timestamps or model the temporal evolution of entities and relations. Specifically, BoxTE [129] extends the static BoxE [166] model by incorporating temporal information through a relation-specific transfer matrix, facilitating the exploration of more complex inference patterns over time. ChronoR [130] associates timestamps with relations, considering each relation-timestamp pair as a rotation that maps the head entity to the tail entity. TComplEx and TNTComplEx [131] extend the third-order tensor to a fourth-order tensor in complex space for reasoning. Notably, TNTComplEx assumes that certain facts remain static over time, separating the TKG into temporal and non-temporal components. Similarly, TeRo [132] incorporates timestamps into the embeddings of head and tail entities in complex space to capture their temporal evolution, and represents the relation as a rotation that maps the head entity to the tail entity.

#### 3.2.1.3 Neural-based methods

Neural-based methods typically use convolutional neural networks (CNNs) or long short-term memory (LSTM) networks to encode timestamps. These encoded timestamps help model the evolution of entities and relations by capturing their intrinsic correlations and temporal dependencies. For instance, TA-TRANSE [133] is a temporal-aware version of TrasnE [74]. It utilizes LSTM to learn time-aware representations of relation, and represents quadruples as a set of triples in the form of  $(h, r_{seq}, t)$ , where  $r_{seq}$  means relation that may include temporal information with a temporal suffix. Similarly, TA-DISTMULT [133] is a temporal extension of DistMult [89], considering the relation with temporal information as a sequence. Additionally, HyTE [134] is an extension of TransH [82], DE-SimplE [135] is an extension of SimplE [90]. These methods often consider temporal constraints to enhance temporal reasoning capabilities. For ex-

ample, TIMEPLEX [136] leverages the recurrent nature of certain facts and the temporal interactions between pairs of relations during expansion. These additional temporal constraints can help assess a quadruple's validity better.

### 3.2.2 Extrapolation-based TKG reasoning

**Task definition:** Given a TKG with facts from  $time_0$  to  $time_T$ , the Extrapolation-based TKG reasoning method aims to predict unknown facts  $(h, r, ?, time_j)$  or  $(?, r, t, time_j)$  that occur in the future ( $time_j > time_T$ ). Extrapolation-based TKG reasoning methods can be categorized into RL-based, rule-guided, and GNN-based.

#### 3.2.2.1 Reinforcement learning-based methods

RL-based methods model path reasoning process through a reinforcement learning framework. For instance, TPPath [137] adds the time information as a separate vector to participate in the iteration of environment and agent. TAgent [138] filters the embeddings of candidate actions through a novel gate mechanism based on temporal information to capture temporal evolutionary patterns. TiTer [139] defines a relative time encoding function to capture the information of timestamps and designs a time-shaped reward based on the Dirichlet distribution to guide the model's learning. CluSTeR [140] proposes a beam search strategy to elicit multiple clues from historical facts and uses graph convolutional networks to deduce answers from the clues.

#### 3.2.2.2 Rule-guided methods

Rule-guided methods derive some temporal logic rules from TKGs and utilize them to predict future facts. The rules provide a structured framework to infer logical conclusions, thereby generating more accurate predictions about future states or events. For example, TLogic [141] automatically mines cyclic temporal logical rules by extracting temporal random walks from the graph. LCGE [142] mines the temporal rules with several time constraint patterns to construct a rule-guided predicate embedding regularization strategy for learning the causality among events. Rule-guided methods can also be integrated with RL-based methods to reduce semantic noise during reasoning and enhance the stability of the model. For example, TPRG [143] proposes a similar concept of temporal rules and has made improvements based on TPPath [137], achieving certain improvements. DREAM [144] proposes a reinforcement learning framework where the agent can receive adaptive rewards by imitating demonstrations at both the semantic and rule levels to eliminate the issue of sparse rewards.

#### 3.2.2.3 GNN-based methods

Recent advancements in temporal knowledge graphs have leveraged GNNs to manage structural and temporal dependencies. Know-Evolve [145] is a classic and the first temporal knowledge graph reasoning model that models the occurrence of facts (edges) as a multivariate point process over time, thereby learning non-linearly evolving entity representations with a deep recurrent network. As with SKGs, GCN [167] is beneficial for TKGR. For example, RE-NET [146] applies GCN [167] to interpret event occurrences as sequences of subgraphs within TKGs, employing an autoregressive model with a neighborhood aggregation function to enhance interpretability. Both RE-GCN [147] and its advanced version, the CEN [148], holistically treat the entire KG sequence to capture the evolutionary dynamics of entities and relations, effectively pinpointing local historical dependencies. Meanwhile, CyGNet [149] focuses on identifying high-frequency entities by exploiting repetitive patterns in historical data using a copy-generation network. On the other hand, CENET [150] differentiates between historical and non-historical dependencies to better identify entities suited for specific queries. While these models excel at capturing specific long-range facts, they often lack high-order connectivity information and dynamic sequential patterns required for a deeper understanding. To address these shortcomings, TiRGN [151] develops different structural encoders to capture sequential and recurring patterns within historical data. Furthermore, HGLS [152] designs a hierarchical graph framework to model long-term dependencies of entities across different timestamps.

### 3.3 Multi-modal knowledge graph reasoning

**Task definition:** The goal of MMKG reasoning methods is similar to SKG reasoning methods, which aims to complete the triplet  $(h, r, t)$  when one of  $h$ ,  $r$ , or  $t$  is missing. In particular, the entity ( $h$  and  $r$ ) could be text or images or has attributes of text and images. The MMKG reasoning methods can be divided into naive fusion MMKG reasoning and multi-modal pre-trained transformer-based (MPT-based) MMKG reasoning methods.

#### 3.3.1 Naive fusion MMKG reasoning methods

Naive fusion MMKG reasoning methods evolve from traditional SKG reasoning methods. They concentrate on the efficient encoding and integration of multi-modal data. The representation of multi-modal data is achieved by either combining each individual modality's representation within its own feature space or by projecting different modal representations into a shared latent space.

The earliest work IKRL [153] uses a neural image encoder to construct representations for all images of an entity. Then, the multiple image representations of an entity are combined with the original structure-based representations and trained like TransE [74], thereby learning multi-modal knowledge representations for reasoning. Inspired by IKRL [153], a translation-based Visual and Linguistic Representation Model (VALR) [154] has been proposed, which defines the energy of the triple as the sum of sub-energy functions that leverage both visual, linguistic and structural representations. Similarly, TransAE [155] combines multi-modal autoencoder with TransE [74] model, where the hidden layer of the autoencoder is used to encode multi-modal data. MKBE [156] designs specialized encoding layers, scoring modules, and decoding layers for data in different modals. THCR [157] complements the relational knowledge by learning a shared latent representation that integrates information across those modalities. MMKRL [158] designs a joint learning framework that can be easily extended to any modality and uses an adversarial strategy to enhance its robustness. RSME [159] automatically encourages or filters the influence of visual context to avoid encoding too much irrelevant information.

#### 3.3.2 MPT-based MMKG reasoning methods

MPT-based MMKG reasoning methods use MPT to encode textual and visual features in a unified architecture. Then, it employs graph encoders to integrate structural knowledge with multi-modal knowledge. For example, VBKG [160] focuses on the co-design of the structural KG model and negative sampling. It consists of an encoding module with VisualBERT [168], a projection module, and a scoring module like TransE [74]. MKGformer [161] utilizes a hybrid transformer architecture with unified input-output and reduces noise from irrelevant images/objects through token-level modal fusion. SGMPT [162] designs a structure-guided fusion module that uses weighted summation and alignment constraint to inject the structural information into both the textual and visual features.

### 3.4 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to reasoning based on symbolic knowledge bases, including (1) # Ent.: Entity number; (2) # Rel.: Relation number; (3) # Time.: Timestamp number; (4) # Facts: Fact number; (5) Type: Knowledge graph type. In particular, the MMKG is represented by specific combinations of modalities. Taking “KG+TXT+IMG” for example, “KG” means the entity has a simple name or ID, “TXT” means the entity has a textual description as attributes, “IMG” means the entity has single or multiple corresponding images as attributes; (6) Domain: The domain of knowledge stored in the KGs; (7) Source: The source of the KGs, and (8) Links: The storage address of the KGs. The statistical results are shown in Table 1.

## 4 Reasoning based on parametric knowledge bases

Since reasoning methods based on parametric knowledge bases are often task-independent, this section reviews them from the perspective of their equipped techniques rather than tasks. These methods mainly perform reasoning in the form of question answering.

| Datasets             | # Ent.     | # Rel.     | # Time. | # Facts       | Type           | Domain          | Source                    | Links                           |
|----------------------|------------|------------|---------|---------------|----------------|-----------------|---------------------------|---------------------------------|
| ATOMIC [169]         | 304,388    | 9          | -       | 785,937       | Static         | Commonsense     | Crowdsourcing             | <a href="https://">https://</a> |
| CODEX.S [170]        | 2,034      | 42         | -       | 36,543        | Static         | General         | Wikidata                  | <a href="https://">https://</a> |
| CODEX.M [170]        | 17,050     | 51         | -       | 206,205       | Static         | General         | Wikidata                  | <a href="https://">https://</a> |
| CODEX.L [170]        | 77,951     | 69         | -       | 612,437       | Static         | General         | Wikidata                  | <a href="https://">https://</a> |
| ConceptNet [171]     | 28,370,083 | 50         | -       | 34,074,917    | Static         | General         | Wikipedia,OpenCyc,WordNet | <a href="https://">https://</a> |
| ConceptNet100K [172] | 78,527     | 34         | -       | 100,000       | Static         | General         | ConceptNet                | <a href="https://">https://</a> |
| DBpedia50K [173]     | 49,000     | 654        | -       | 43,756        | Static         | General         | Wikipedia                 | <a href="https://">https://</a> |
| FB15k-237 [174]      | 14,541     | 237        | -       | 310,116       | Static         | General         | Freebase                  | <a href="https://">https://</a> |
| Hetionet [175]       | 47,031     | 24         | -       | 2,250,197     | Static         | Biomedical      | public datasets           | <a href="https://">https://</a> |
| NELL-995 [100]       | 75,492     | 200        | -       | 154,213       | Static         | General         | Web                       | <a href="https://">https://</a> |
| OpenBioLink [176]    | 180,992    | 28         | -       | 4,192,002     | Static         | Biomedical      | public datasets           | <a href="https://">https://</a> |
| UMLS [177]           | 135        | 49         | -       | 6752          | Static         | Biomedical      | human experts             | <a href="https://">https://</a> |
| Nation [177]         | 14         | 55         | -       | 1,592         | Static         | Social Sciences | human experts             | <a href="https://">https://</a> |
| WN18 [74]            | 40,943     | 18         | -       | 151,442       | Static         | Semantics       | WordNet                   | <a href="https://">https://</a> |
| YAGO3-10 [178]       | 123,182    | 37         | -       | 1,079,040     | Static         | General         | YAGO                      | <a href="https://">https://</a> |
| IMDB-13-3SP [179]    | 3,244,455  | 14         | 30      | 627,096       | Temporal       | Movie           | IMDB                      | <a href="https://">https://</a> |
| IMDB-30SP [179]      | 243,148    | 14         | 3       | 7,923,773     | Temporal       | Movie           | IMDB                      | <a href="https://">https://</a> |
| YAGO-3SP [179]       | 27,009     | 37         | 3       | 130,757       | Temporal       | General         | YAGO                      | <a href="https://">https://</a> |
| DBpedia-3SP [179]    | 66,967     | 968        | 3       | 201,089       | Temporal       | General         | DBpedia                   | <a href="https://">https://</a> |
| YAGO11k [134]        | 10,623     | 10         | 189     | 161,540       | Temporal       | General         | YAGO                      | <a href="https://">https://</a> |
| Wikidata12k [134]    | 12,554     | 24         | 232     | 3,419,607     | Temporal       | General         | Wikidata                  | <a href="https://">https://</a> |
| GDELT-small [180]    | 500        | 20         | 366     | 3,419,607     | Temporal       | Social Science  | GDELT                     | <a href="https://">https://</a> |
| ICEWS14 [180]        | 7,128      | 230        | 365     | 90,730        | Temporal       | Social Science  | ICEWS                     | <a href="https://">https://</a> |
| ICEWS05-15 [180]     | 10,488     | 251        | 4017    | 479,329       | Temporal       | Social Science  | ICEWS                     | <a href="https://">https://</a> |
| ICEWS14 [180]        | 7,128      | 230        | 365     | 90,730        | Temporal       | Social Science  | ICEWS                     | <a href="https://">https://</a> |
| FB-IMG [154]         | 11,757     | 1231       | -       | 350,293       | KG+TXT+IMG     | General         | Freebase                  | <a href="https://">https://</a> |
| IMGpedia [181]       | 14,765,300 | 44,295,900 | -       | 3,119,207,705 | KG+TXT+IMG     | General         | DBpedia,Wikimedia         | <a href="https://">https://</a> |
| MMKG-DB15K [182]     | 14,777     | 279        | -       | 99,028        | KG+Numeric+IMG | General         | Freebase,DBpedia          | <a href="https://">https://</a> |
| MMKG-Yago15k [182]   | 15,283     | 32         | -       | 122,886       | KG+Numeric+IMG | General         | Freebase,YAGO             | <a href="https://">https://</a> |
| MKG-W [183]          | 15,000     | 169        | -       | 42,746        | KG+TXT+IMG     | General         | Wikipedia                 | <a href="https://">https://</a> |
| MKG-Y [183]          | 15,000     | 28         | -       | 26,638        | KG+TXT+IMG     | General         | YAGO                      | <a href="https://">https://</a> |
| RichPedia [184]      | 29,985     | 3          | -       | 119,669,570   | KG+IMG         | General         | WikiPedia                 | <a href="https://">https://</a> |
| FB15k-237-IMG [161]  | 14,541     | 237        | -       | 310,116       | KG+IMG         | General         | Freebase                  | <a href="https://">https://</a> |
| WN18-IMG [161]       | 14,541     | 18         | -       | 151,442       | KG+IMG         | General         | WordNet                   | <a href="https://">https://</a> |

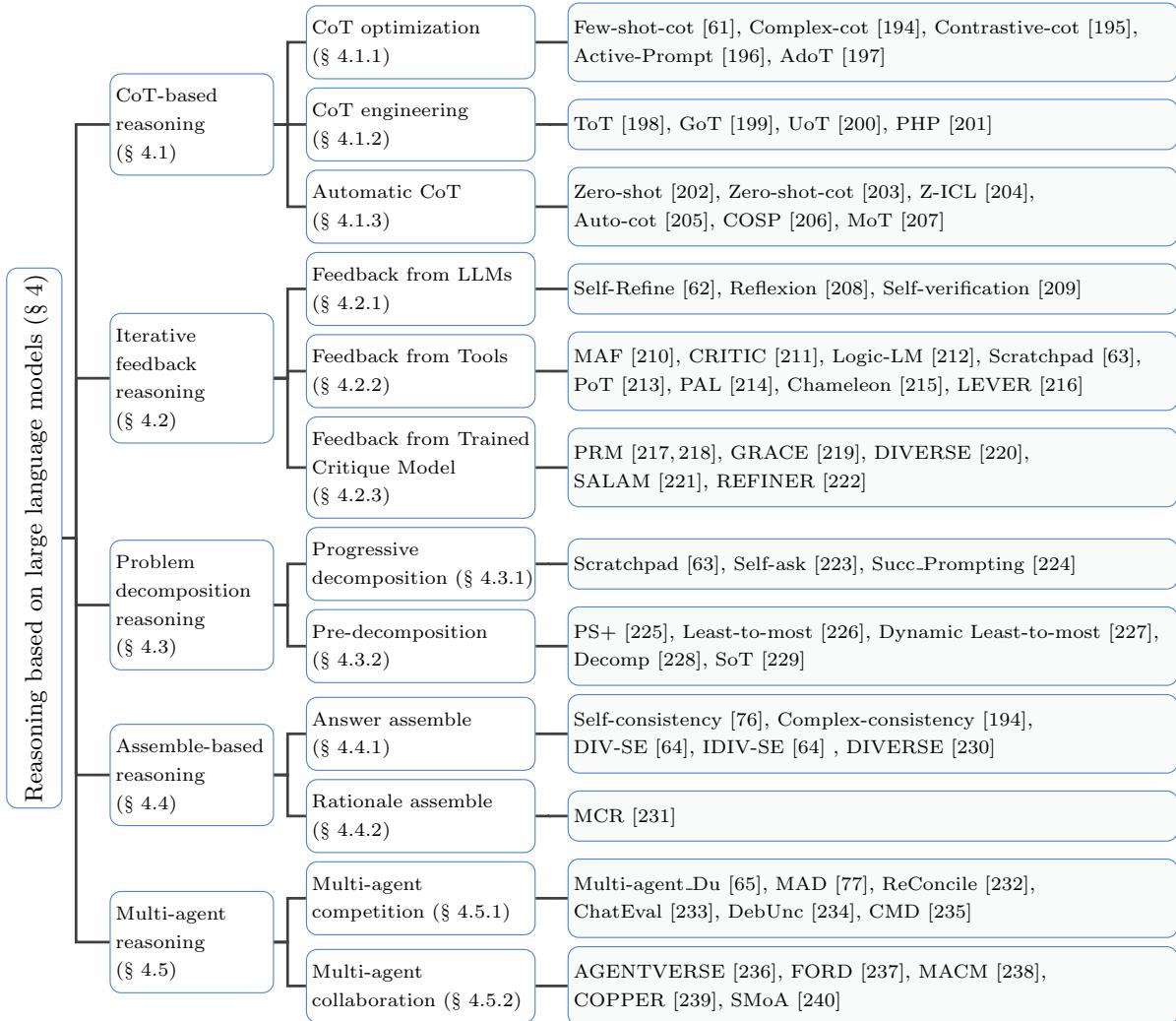
**Table 1** Dataset statistics of reasoning based on symbolic knowledge bases.

**Task definition:** Given a knowledge-intensive question, which requires deep understanding and reasoning capability to answer correctly, this type of method is required to leverage the knowledge encoded in parametric knowledge bases to reason for the final answer.

Parametric knowledge bases mainly refer to PLMs. Based on the size of their parameter scales, PLMs can be divided into small language models (SLMs) and large language models (LLMs). SLMs-based reasoning methods [185] need to fine-tune on task-oriented or domain-specific data to enhance their performance. For example, LoP [186] trains RoBERTa [42] on both implicit pre-trained knowledge and explicit free-text statements to symbolic reasoning. The method [67] fine-tunes the GPT-2 [187] to generate full step-by-step solutions to arithmetic reasoning. Though these approaches have shown better performance than traditional rule-based [188, 189], symbolic-based [190, 191], and statistical-based [192, 193] methods, their reasoning ability has been limited by the size of SLMs. Moreover, fine-tuning SLMs requires high-quality training data, which is quite labor-intensive.

Recently, LLMs-based reasoning methods have shown impressive abilities, and prompting is the primary way to interact with LLMs. Compared with SLMs, LLMs possess strong generalization and in-context learning capabilities by providing a few demonstrations (i.e., few-shot learning) or instruction to solve new problems without any demonstrations (i.e., zero-shot learning). Therefore, we mainly investigate reasoning methods based on LLMs.

Many prompting methods have been proposed for reasoning problems [197, 208]. The first attempt is made by [202], which developed a zero-shot prompting method by adding a natural language description of the task in the prompt. Some follow-up methods try to optimize the prompting strategy from the perspective of Chain-of-Thought (CoT) [61], Iterative feedback [62], Problem decomposition [63], Assem-



**Figure 5** Taxonomy of reasoning methods based on large language models.

ble [76], and multi-agent [77]. These methods are widely applied to mathematical, commonsense, and symbolic reasoning tasks. The overall taxonomy of reasoning methods based on parametric knowledge bases is shown in Figure 5.

#### 4.1 CoT-based reasoning

Recent studies [61, 203, 226] find that generating a series of intermediate reasoning steps (also known as CoT and rationale) significantly improves the ability of LLMs to perform complex reasoning. The intermediate reasoning steps of CoT-series methods contribute to enhancing the logical consistency of the reasoning processes before reaching a conclusion. In this way, CoT-series methods significantly improve the LLMs' ability to perform tasks that require multi-step reasoning and deep understanding. There are three types of CoT-series methods: CoT optimization, CoT engineering, and automatic CoT methods.

##### 4.1.1 CoT optimization

CoT optimization methods construct the question-rationale pairs as demonstrations to guide the LLMs to reason step by step. Few-shot-cot [61] adopts some questions and manually constructs CoT as demonstrations for the first time. Following this line, the CoT optimization methods try to optimize the CoT in demonstrations from different perspectives. For instance, Complex-cot [194] finds that demonstrations with higher reasoning complexity achieve substantially better performance on multi-step reasoning. Hence, it constructs CoT with more reasoning steps in demonstrations. Inspired by how humans can

learn from both positive and negative examples, Contrastive-cot [195] provides both positive and negative demonstrations to enhance the reasoning of LLMs. To determine which questions are the most important and helpful to annotate from a pool of task-specific questions, Active-Prompt [196] proposes an uncertainty-based annotation strategy, which can reduce the model's uncertainty and help elicit the reasoning ability of LLMs. To solve the mismatch between the question difficulty and the methods' complexity, AdoT [197] first presents a difficulty measuring approach for questions that computes the syntactic and semantic complexity of their rationales. Then, it proposes a demonstration set construction and a difficulty-adapted retrieval strategy to adaptively construct reasonable demonstrations based on the difficulty of the questions.

#### 4.1.2 *CoT engineering*

CoT engineering methods are devoted to designing more complex CoT reasoning procedures on the top single reasoning process to help LLMs generate more accurate final answers. Inspired by cognitive science, which characterizes problem-solving as a search through a combinatorial problem space, ToT [198] actively maintains a tree of thoughts, where each thought is a coherent language sequence that serves as an intermediate step toward problem-solving. GoT [199] models the information generated by LLMs as an arbitrary graph, where information units are vertices, and edges correspond to dependencies between these vertices. GoT enables combining arbitrary LLM thoughts into synergistic outcomes, distilling the essence of whole networks of thoughts, or enhancing thoughts using feedback loops. The information needed to solve the task is not initially given in many reasoning-related applications. To enhance LLMs in actively seeking information, UoT [200] incentivizes a model to seek information in a way that maximally reduces the amount of information it does not know. To optimize the generated answer progressively, PHP [201] performs automatic multiple interactions between queries and LLMs by using previously generated answers as hints.

#### 4.1.3 *Automatic CoT*

The aforementioned two types of methods achieve excellent performance, but they rely on manually constructed demonstrations, which may generalize poorly between data from different domains. Hence, the automatic CoT methods try to design general instructions to trigger multi-step reasoning or construct pseudo-demonstrations to guide LLMs under a zero-shot setting. For instance, Zero-shot-cot [203] concatenates a simple but effective instruction “Let's think step by step” after question, which can activate the inherent multi-step reasoning capability of LLMs. To solve the problem that performance drops significantly when no demonstration is available, Z-ICL [204] constructs pseudo-demonstrations from a raw text corpus. It retrieves relevant text from the corpus using the nearest neighbor search and then adjusts the pseudo-demonstrations with physical neighbor and synonym labeling to avoid the copying effect. Auto-cot [205] samples questions with diversity and automatically generates rationales to construct demonstrations. COSP [206] constructs demonstrations from the LLM zero-shot outputs via carefully designed criteria that combine consistency, diversity, and repetition. MoT [207] pre-thinks on the unlabeled dataset and saves the high-confidence thoughts through answer entropy as external memory. During inference, MoT lets the LLM recall relevant memory to help itself reason and answer it.

### 4.2 Iterative feedback reasoning

Inspired by the human behavior of trial, checking errors, and correcting them during reasoning, some researches focus on utilizing iterative feedback to correct mistakes in the reasoning steps to enhance the reasoning capabilities of LLMs [241]. Using iterative feedback to improve reasoning typically involves three steps: 1) reasoning, 2) critique and feedback, and 3) reasoning refinement. The sources of feedback in these methods mainly include LLMs themselves, various tools (including calculators, search engines, logic tools, and code interpreters), and trained critique models.

#### 4.2.1 *Feedback from LLMs*

Some early studies discovered that LLMs can check errors in their reasoning process, known as the ability of “self-reflection”. Inspired by this, Self-Refine [62] explores how to achieve iterative feedback and refinement based on the LLM itself to improve the quality of reasoning. Reflexion [208] employs an iterative process of “Trajectory→Evaluation→Reflection→Next Trajectory” to iteratively enhance the

reasoning process. Self-verification [209] implements “Forward Reasoning” and “Backward Verification” to validate the reasoning process and selects the highest-quality reasoning results based on evaluation scores. However, it should be noted that recent studies [242, 243] have suggested that this “self-reflection” approach may be constrained by the model’s inherent reasoning capabilities, potentially hindering improvements in reasoning quality.

#### 4.2.2 Feedback from tools

Research has explored integrating various tools into feedback modules to help correct reasoning errors. Different types of reasoning errors necessitate different tools. For example, calculators are often used to provide precise arithmetic results as feedback for arithmetic tasks [210, 211], while search engines are employed to verify factual errors [211, 215]. For logical reasoning tasks, Logic-LM [212] suggests using logical tools like First-order Logic Provers to identify logic errors and provide feedback. Moreover, considering that the pre-training corpora of LLMs contain a substantial amount of structured code, some studies suggest transforming reasoning tasks into code form and then using code interpreters to provide feedback [63, 213–216]. All these methods focus on transforming the output text of LLMs into formats suitable for inputting into various tools, thus obtaining precise external feedback and enhancing the quality of reasoning.

#### 4.2.3 Feedback from trained critique model

Earlier studies [217, 218] demonstrated that process-based reward models outperform outcome-based reward models when providing feedback for mathematical reasoning tasks. Building on this, GRACE [219] and DIVERSE [220] propose training critic models capable of selecting optimal intermediate reasoning steps as feedback. Furthermore, SALAM [221] and REFINER [222] explore the idea of training models that generate error analyses in natural language form as feedback, which can be used to refine reasoning steps iteratively. All these approaches involve training task-specific critique models, enabling them to fully leverage the available training data for specific reasoning tasks. As a result, they achieve significantly improved feedback quality and corrective effectiveness compared to relying on general-purpose LLMs for feedback.

### 4.3 Problem decomposition reasoning

When solving complex problems, decomposing a problem into multiple simpler or more detailed sub-problems is an important strategy employed by humans. The general process of problem decomposition-related methods is decomposing a complex problem into several simpler sub-problems. These sub-problems are then solved one by one. Finally, the answers to the sub-problems are combined to obtain the answers to the original problem. When the task is complex or the individual reasoning steps are hard to learn, this method often yields superior results. However, when dealing with simple problems, further decomposing them may not be very meaningful and increase time overhead. There are two types of problem decomposition methods: progressive decomposition and pre-decomposition methods.

#### 4.3.1 Progressive decomposition

Progressive decomposition methods alternately decompose the questions and reason for the sub-questions step-by-step. For instance, Succ\_Prompting [224] iteratively decomposes the complex question into the following simple question to answer and then repeats until the complex question is answered. Scratchpad [63] allows the model to produce an arbitrary sequence of intermediate tokens, which it calls a scratchpad, before producing the final answer. For example, on addition problems, the scratchpad contains the intermediate results from a standard long addition algorithm. Self-ask [223] asks itself follow-up questions before answering the initial question, which will narrow the compositionality gap that models can correctly answer all sub-problems but not generate the overall solution.

#### 4.3.2 Pre-decomposition

Unlike the progressive decomposition methods, the pre-decomposition methods decompose the questions before reasoning. PS+ [225] devises a plan to divide the entire task into smaller subtasks and then carries out the subtasks according to the plan. Least-to-most [226] breaks down a complex problem into

a series of simpler subproblems and then solves them in sequence. To promote the practicality of Least-to-most, Dynamic Least-to-most [227] obtain the problem reduction via a multi-step syntactic parse of the input. Furthermore, it dynamically selects exemplars from a fixed pool such that they collectively demonstrate as many parts of the decomposition as possible. Decomp [228] argues that few demonstrations of the complex task aren't sufficient for current models to learn to perform all necessary reasoning steps as tasks become more complicated. Hence, it solves complex tasks by instead decomposing them into simpler sub-tasks and delegating these to sub-task specific LLMs, with both the decomposer and the sub-task LLMs having their own few-shot prompts. SoT [229] guides the LLM to derive a skeleton first by itself. Based on the skeleton, the LLMs then complete each point in parallel.

#### 4.4 Assemble-based reasoning

The core idea of assemble-related methods is that a complex reasoning problem typically admits multiple different ways of thinking, leading to its unique correct answer [76]. As shown in Figure 4 (e), typical answer assemble methods first generate multiple different rationales with answers and then choose the most consistent one as the final answer. Furthermore, a few rationale assemble methods try to leverage the difference between multiple reasoning processes to enhance reasoning performance. The assemble-related methods demonstrate excellent performance. Moreover, they can be easily integrated with other classes of methods, such as CoT-series. However, due to the need to generate multiple reasoning processes, the overhead of this class of methods is relatively high.

##### 4.4.1 Answer assemble

Self-consistency [76] first samples a diverse set of rationales instead of only taking the greedy one and then selects the most consistent answer by marginalizing out the sampled reasoning paths. Instead of voting among all rationales, Complex-consistency [194] votes among top-K complex rationales with more steps. To leverage variations of the input prompt to introduce the diversity needed for assembling, DIV-SE [64] automatically improves prompt diversity by soliciting feedback from the LLM to ideate approaches that are apt for the problem. Then, it assembles the diverse prompts across multiple inference calls. To reduce the inference costs of DIV-SE, IDIV-SE [64] combines all approaches within the same prompt and aggregates all resulting outputs to leverage diversity. Similar to DIV-SE [64], DIVERSE [230] proposes to increase the diversity of rationales by sampling from a single prompt and varying the prompt itself. It first uses a verifier to score the quality of each rationale and guide the voting mechanism. Then, it assigns a fine-grained label to each step of the reasoning path and uses a step-aware verifier to attribute the correctness or wrongness of the final answer to each step.

##### 4.4.2 Rationale assemble

The answer assemble methods generate multiple rationales and aggregate them through a voting mechanism over the final answers, which ignore the information in intermediate steps. Furthermore, although the answer assemble methods perform well, they do not provide a unified explanation for the predicted answer. Hence, MCR [231] focuses on rationale assemble, which leverages the relations between intermediate steps across multiple rationales. MCR mixes information between multiple relations and selects the most relevant facts to generate an explanation and predict the answer. Unlike answer assemble methods, sampled rationales are used not for their predictions but to collect evidence from multiple rationales. MCR concatenates the intermediate steps from each rationale into a unified context, passed to a meta-reasoner model along with the original question. The meta-reasoner model prompts to meta-reason on multiple rationales and produces a final answer with an explanation. In this way, MCR could combine facts from multiple chains to produce the final answer with an explanation of the answer's validity.

#### 4.5 Multi-agent reasoning

Multi-agent reasoning draws inspiration from *society of minds* concepts [244] found in multi-agent systems. In contrast to single-agent methods, such as CoT and ToT, multi-agent reasoning methods emphasize the diversity of ideas and the importance of communication, adversarial interaction, and collaboration among multiple agents. In the reasoning stage, multi-agents express their individual viewpoints and interact in various ways (such as through debate, collaboration, and community communication) to

arrive at a final solution. The divergent thinking of multi-agent reasoning determines that (i) The distorted thinking of one agent can be rectified by other agents, (ii) the supplementation of one agent's resistance to change by others, and (iii) the reception of external feedback by each agent from others.

A limitation of multi-agent reasoning is that it requires more time cost, as agents often need to participate in multiple rounds of interaction to present and counter arguments. Additionally, current LLM-based agents may struggle to maintain coherence and relevance in long-context scenarios, leading to potential misunderstandings and context loss. Enhancing the long-text modeling capabilities of large language models remains challenging for future research. Multi-agent reasoning methods can be categorized into multi-agent competition and multi-agent collaboration.

#### 4.5.1 Multi-agent competition

Multiple LLM-based agents conduct independent thinking and reasoning in multi-agent competition methods. When agents hold differing opinions, they examine each other's responses and adapt their answers accordingly. Through several rounds of adversarial interaction, the multi-agent system ultimately reaches a conclusion that satisfies the internal logic of each agent while aligning with the feedback from other agents.

Recently, abundant multi-agent competition methods are designed to explore how to unleash the potential of multi-agent systems. For instance, Multi-agent\_Du [65] is a role-symmetric multi-agent competition framework where different agents engage in spontaneous discussion. MAD [77] introduced different roles, such as judges and debaters, into the debate process. This represents a role-asymmetric multi-agent debate architecture. RECONCILE [232] facilitates deeper multi-agent discussions by introducing confidence assessments and persuasive explanations in the form of roundtable meetings. ChatEval [233] adopts three distinct communication strategies within its diversified role communication process: one-on-one, simultaneous-talk, and simultaneous-talk-with-summarizer. DebUnc [234] enhances the reliability of multi-agent debates by quantifying and conveying agents' uncertainties throughout the debate process, reducing the hallucination phenomena often associated with LLMs. Additionally, research evaluating multi-agent competition has shown that, as demonstrated by CMD [235], effective prompt engineering can enable a single agent to achieve performance comparable to multi-agent discussions. Multi-agent discussions, however, have a distinct advantage in contexts lacking examples, and discussions involving multiple LLMs can enhance the performance of weaker LLMs.

#### 4.5.2 Multi-agent collaboration

Multi-agent LLM collaboration involves agents working together cooperatively to solve a given problem. AGENTVERSE [236] simulates the problem-solving process of human groups through mechanisms such as expert recruitment, collaborative decision-making, and tool utilization. FORD [237] explores the issue of mutual consistency among multiple LLMs by introducing a formalized debate mechanism, illuminating both the potential and challenges inherent in LLM collaboration. MACM [238] first abstracts the conditions and objectives of a problem, then employs a multi-agent interaction system to iteratively uncover new conditions that facilitate the achievement of the goals, ultimately solving the problem. COPPER [239] enhances the collaborative capabilities of multi-agent systems based on LLMs through a self-reflection mechanism. This framework involves training a shared reflector and utilizes a counterfactual proximal policy optimization (PPO) mechanism to optimize the quality of reflections. SMoA [240] introduces sparse to optimize the fully connected structures commonly found in traditional multi-agent methods, thereby balancing performance and computational cost. Social\_Agent [245] explores the collaboration mechanisms among agents and analyzes these mechanisms from a social psychology perspective.

### 4.6 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to reasoning based on parametric knowledge bases, including (1) Domain: The domain of knowledge corresponding to the datasets; (2) # Ques.: Question number; (3) Q&A source: The main construction methods of questions and answers. They are mainly divided into three categories: "Generate", "Expert", and "Crowdsourcing". "Generate" refers to the design of programs for automated generation, "Expert" refers to direct crawling from professional websites or carefully designed by domain experts, and "Crowdsourcing" refers to completion by crowdsourcing workers with general cultural levels; (4) Rationale: Whether they contain

rationales; (5) Answer type: The form of answers; (6) Links: The storage address of the datasets. The statistical results are shown in Table 2.

| Datasets            | Domain      | # Ques. | Q&A source    | Rationale | Answer type | Links                           |
|---------------------|-------------|---------|---------------|-----------|-------------|---------------------------------|
| AQUA [246]          | Arithmetic  | 254     | Generate      | ✓         | Option      | <a href="https://">https://</a> |
| GSM8K [247]         | Arithmetic  | 1319    | Crowdsourcing | ✗         | Number      | <a href="https://">https://</a> |
| SVAMP [248]         | Arithmetic  | 1000    | Generate      | ✓         | Number      | <a href="https://">https://</a> |
| AddSub [249]        | Arithmetic  | 395     | Expert        | ✓         | Number      | <a href="https://">https://</a> |
| MultiArith [250]    | Arithmetic  | 600     | Expert        | ✓         | Number      | <a href="https://">https://</a> |
| SingleEq [251]      | Arithmetic  | 508     | Expert        | ✓         | Number      | <a href="https://">https://</a> |
| Last Letters [61]   | Symbolic    | 500     | Generate      | ✗         | String      | <a href="https://">https://</a> |
| Coin Flip [61]      | Symbolic    | 500     | Generate      | ✗         | Yes/No      | <a href="https://">https://</a> |
| CommonsenseQA [252] | Commonsense | 1221    | Crowdsourcing | ✗         | Option      | <a href="https://">https://</a> |
| StrategyQA [253]    | Commonsense | 2290    | Crowdsourcing | ✓         | Yes/No      | <a href="https://">https://</a> |

Table 2 Dataset statistics of reasoning based on parametric knowledge bases.

## 5 Collaborative reasoning based on symbolic and parametric knowledge bases

In this section, we are devoted to investigating collaborative reasoning methods based on symbolic and parametric knowledge bases. These methods mainly perform reasoning in the form of question answering. Generally, given a knowledge-intensive question, this type of method is required to leverage the knowledge in symbolic and parametric knowledge bases collaboratively to reason for the correct answer.

Based on the structure of the symbolic knowledge bases, these question answering tasks can be categorized into graph-based reasoning, table-based reasoning, text-based reasoning, and heterogeneous reasoning. The symbolic knowledge bases store knowledge in the form of structured graphs, structured tables, and unstructured text in graph-based, table-based, and text-based reasoning tasks, respectively. In particular, heterogeneous reasoning investigates how to leverage symbolic knowledge from multiple heterogeneous symbolic knowledge bases, such as KGs, tables, and text. The overall taxonomy of collaborative reasoning methods based on symbolic and parametric knowledge bases is shown in Figure 6.

### 5.1 Graph-based reasoning

The tasks of graph-based reasoning include knowledge graph question answering (KGQA) and temporal knowledge graph question answering (TKGQA), where symbolic knowledge is stored in SKGs and TKGs, respectively.

#### 5.1.1 Knowledge graph question answering

**Task definition:** Given a question and an SKG, KGQA methods are required to understand the intent of the question via the parametric knowledge bases and retrieve the entity nodes from the SKG as answers.

KGQA methods can be categorized into two classes: semantic parsing-based (SP-based) methods and information retrieval-based (IR-based) methods [36]. SP-based methods aim to parse the questions into the logical forms (such as SPARQL, S-expression and query graph) to yield the correct answer. IR-based methods construct a question-specific subgraph of the SKG and retrieve the most matching answers. In recent years, most methods utilize PLMs to integrate a substantial amount of external knowledge. Due to the introduction of parametric knowledge, the level of intelligence has been significantly enhanced, leading to considerable improvements in accuracy and task versatility.

##### 5.1.1.1 Semantic parsing-based methods

SP-based methods aim to learn the semantic matching between natural language questions and logical forms, which mainly involves the following steps: the method understands the natural language question, converts it into a logical form, aligns it with the existing knowledge in given SKG, and finally executes it to derive the correct answer. Early SP-based methods only apply to independent and identically distributed scenarios and perform poorly in solving problems that require commonsense knowledge and

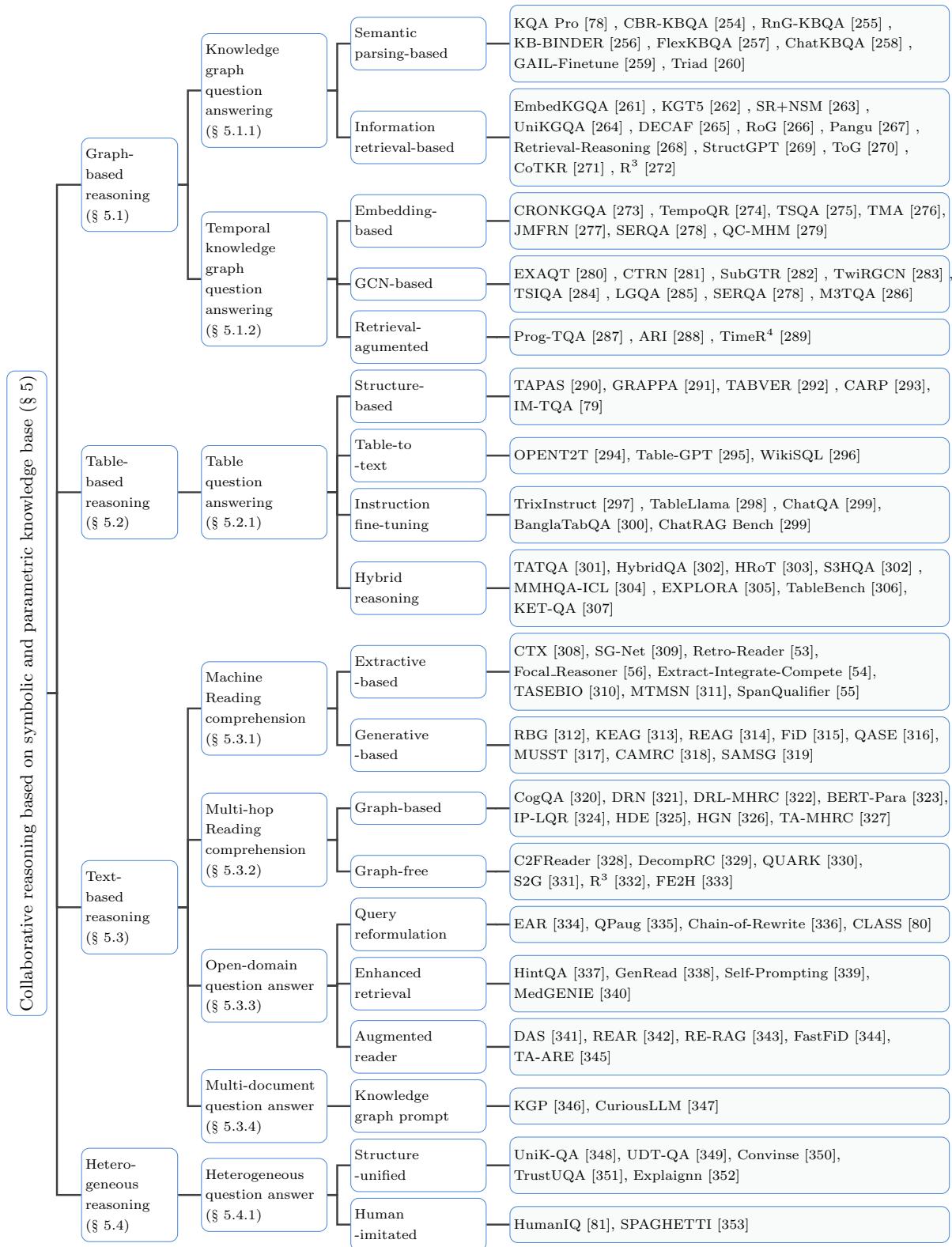
**Figure 6** Taxonomy of collaborative reasoning methods based on symbolic and parametric knowledge bases.

exhibit relatively weak intelligence. So most SP-based methods fine-tune PLMs on specific data to convert natural language questions to logical form.

For example, KQA Pro [78] introduces a compositional and interpretable programming language KoPL to represent the reasoning process of complex questions fine-tunes BART [69] to achieve compositional reasoning. CBR-KBQA [254] uses ROBERTA-base [42] to encode each question independently and generate a logical form for a new question by retrieving cases that are relevant to it with the pre-trained ROBERTA-base weights. RnG-KBQA [255] introduces T5 [68] to construct the final logical form based on the questions and the high-ranked candidate logical forms, demonstrating excellent performance even when dealing with questions involving unseen schema items.

Several SP-based methods utilize LLMs to parse natural language questions into logical forms in a few-shot in-context learning setting. For example, KB-BINDER [256] generates drafts with LLM as preliminary logical forms and then binds the entities, relations, and schema items of the drafts to SKG iteratively. FlexKBQA [257] introduces a self-training approach with execution guidance, using the LLM to convert logical forms into natural language questions and utilizing unlabeled user questions iteratively.

In addition, fine-tuning LLM also makes sense. For example, ChatKBQA [258] proposes generating the logical form with fine-tuned LLMs first, then retrieving and replacing entities and relations through an unsupervised retrieval method. GAIL-Finetune [259] fine-tunes Llama-2-7B [354] to produce expert-level sample and evaluate the authenticity and relevance of the sequences to tackle the challenges in low-resource KGQA scenario. Triad [260] utilizes an LLM-based agent with three different roles for KBQA tasks.

In general, knowledge for KGQA tasks not only includes professional knowledge that can be modeled through SKGs and limited training samples but also general knowledge. Therefore, fine-tuning PLM, or directly utilizing the powerful LLM, can overcome difficulties in collecting training samples and understanding diversified natural language questions in the real world. However, there are also deviations between parametric general knowledge and symbolic professional knowledge, and exploration of this issue is still in the early stages.

#### 5.1.1.2 *Information retrieval-based methods*

IR-based methods treat the KGQA task as a binary classification of nodes in the SKG and demonstrate superior performance compared to SP-based methods, although they sacrifice interpretability. Early IR-based methods perform poorly because they lack sufficient understanding of user questions and the guidance of common sense knowledge during the reasoning process. Hence, recent advanced IR-based methods generally apply PLMs to model questions and subgraphs of the SKG.

For example, EmbedKGQA [261] has been proposed to handle SKG sparsity, where ComplEx [91] embeddings are trained to represent SKG elements and RoBERTa [42] embedding is used to represent the question. KGT5 [262] considers both SKG reasoning and KGQA as sequence-to-sequence tasks, where a simple Transformer that has the same architecture as T5-small [68] has been trained to achieve excellent performance. SR+NSM [263] utilizes RoBERTa [42] to encode the question and relations in SKG iteratively to expand paths. Then it could construct subgraph with low size but high answer coverage to find answers. UniKGQA [264] combines a PLM with an ultra-simple GNN to transfer the retrieved knowledge to the reasoning phase. DECAF [265] constructs retriever and reader based on FiD-large retriever [355] to generate both logical forms and direct answers jointly.

Recently, several methods have adopted the retrieval-augmented generation (RAG) paradigm because LLMs can simultaneously model both user questions and SKG elements to perform simple deductive reasoning. For example, RoG [266] proposes a planning-retrieval-reasoning framework, which fine-tunes LLaMA2-Chat-7B [354] with relation paths and valid reasoning paths in SKGs. Then it can generate reasoning paths for faithful reasoning. Similarly, Retrieval-Reasoning [268] decomposes the problem into retrieval and reasoning modules and then fine-tunes LLM at three levels: entity, relation, and graph. Pangu [267] leverages the discriminative capabilities of the LLM for context-based language understanding. The symbolic agent explores SKG to construct effective plans incrementally, and the LLM agent evaluates the reasonableness of candidate plans to guide the search process. StructGPT [269] solves KGQA based on structured data, where the facts in SKG could be linearized into LLM to reason naturally. ToG [270] treats LLM as an agent capable of exploring SKG and performing reasoning with retrieved knowledge. The agent iteratively executes beam search on the KG, discovers the most promising

reasoning paths, and returns the most likely reasoning results. CoTKR [271] rewrites retrieved subgraphs into natural language formats comprehensible to LLMs. R<sup>3</sup> [272] surfaces the commonsense knowledge relevant to the question from LLMs and uses it to guide the SKG pruning to find answers.

Overall, IR-based methods require identifying supportive evidence to answer the question directly. In contrast, the parametric knowledge within PLM is used to learn the user's intent and retrieve the relevant subgraph, reducing semantic noise while maintaining a high recall rate of supportive evidence. More importantly, introducing PLM can make the retrieval and denoising processes more transparent and maintain certain performance in few-shot or even zero-shot scenarios.

### 5.1.2 Temporal knowledge graph question answering

**Task definition:** Given a temporal question and a TKG, TKGQA methods are required to understand the intent and temporal constraints of the question via the parametric knowledge bases and retrieve the entity nodes or timestamps from the TKG as answers.

The primary solution for TKGQA involves integrating the knowledge of TKGs and PLMs. Some methods use PLM and pre-trained TKG embeddings to match questions and entities and timestamps, known as embedding-based methods. Some other methods utilize PLM and GCN [167] to learn the features of TKG elements, known as GCN-based methods. In recent years, there have also been methods utilizing LLMs by converting the facts from TKGs into text, which are named retrieval-augmented methods because they primarily enhance the reasoning capabilities of LLMs by accurately retrieving useful knowledge from TKGs.

#### 5.1.2.1 Embedding-based methods

Embedding-based methods utilize existing TKG model to derive embeddings of TKG elements and utilize PLM to derive embeddings of questions. By modeling the matching between them, the answers could be inferred based on the similarity between embeddings of given question and all TKG elements.

A classic embedding-based method is CRONKGQA [273], which builds on EmbedKGQA [261] by employing an advanced temporal knowledge graph reasoning model to derive embeddings of entities and timestamps. It uses PLM to obtain embeddings of entity/time mentioned in the question, models the question as a “virtual relation”, and predicts missing entities and timestamps in the TKG. Similarly, QC-MHM [279] is more refined in handling questions and TKGs. It first injects temporal order information into timestamp embeddings, modifying TComplEx [131] to obtain the embeddings of the entity, relation, and timestamp. It then inputs the sentence and SPO (subject, predicate or relation, and object) into Sentence-BERT [356] to obtain the embedding vectors and model the matching between questions and SPO. Other similar methods include TempoQR [274], TSQA [275], TMA [276], JMFRN [277], and SERQA [278].

The advantage of embedding-based methods lies in their more natural thought process, with a lighter model that can better model the question and match it with TKG. However, the disadvantage is that they struggle with complex temporal constraints and temporal relational terms. Complex temporal constraints require the utilization of multiple factual quadruples, and temporal relational terms are highly sensitive to model.

#### 5.1.2.2 GCN-based methods

GCN-based methods do not leverage existing TKG reasoning models to incorporate knowledge from TKGs, and they learn the matching between questions and TKG subgraphs. They utilize PLM and GCN [167] to learn embeddings of questions and features of a subgraph of TKG, respectively. Then, they cast answer prediction into a node classification task. Compared to embedding-based methods, GCN-based methods can model various constraints within complex problems and retain a more complete subgraph of the TKG.

For example, EXAQT [280] utilizes fine-tuned BERT models and GCN [167] to identify relevant facts. It specifically employs Group Steiner Trees to compute question-relevant compact subgraphs within the KG. Additionally, relational graph convolutional network has been constructed to predict answers. Similarly, GenTKGQA [357] first leverages a LLM and a pre-trained temporal graph neural network to model question and extract information from the subgraph, respectively. Then, it performs instruction tuning to enable complex temporal reasoning. Other similar methods include SubGTR [282], TSIQA [284], CTRN [281], TwiRGCN [283], M3TQA [286] and LGQA [285].

### 5.1.2.3 Retrieval-augmented methods

Retrieval-augmented methods primarily rely on the in-context learning ability and powerful generation capability of LLM, where there is no need for instruction tuning. At the same time, the most relevant knowledge is retrieved from the TKG and combined with the LLM's knowledge to complete complex reasoning tasks collaboratively. For example, Prog-TQA [287] uses a LLM to understand questions and generate corresponding program drafts with symbolic operators as logical forms, given a few examples. With a self-improvement strategy, the quality of these logical forms is enhanced to yield the final answers. Similarly, ARI [288] improves the LLM's capacity to integrate abstract methodologies derived from historical experience. TimeR<sup>4</sup> [289] differentiates the knowledge of TKG into temporal knowledge and factual knowledge and then improves retrieval accuracy through modules such as retrieval, rewriting, and ranking.

The advantage of retrieval-augmented methods lies in their emphasis on retrieving TKG elements. By textualizing the knowledge within the TKG to reduce hallucinations in LLMs and enhance their reasoning capabilities, they achieve breakthroughs in performance than embedding-based methods and GCN-based methods. However, due to LLM's insufficient sensitivity to temporal knowledge, they still face challenges regarding knowledge integration and complex temporal reasoning.

### 5.1.3 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to graph-based reasoning, including (1) Domain: The domain of knowledge corresponding to the datasets; (2) Question type: The type of questions in the datasets; (3) # Ques.: Question number; (4) Q&A source: The main construction methods of questions and answers. They are mainly divided into three categories: “Generate”, “Expert”, and “Crowdsourcing”. “Generate” refers to the design of programs for automated generation, “Expert” refers to direct crawling from professional websites or carefully designed by domain experts, and “Crowdsourcing” refers to completion by crowdsourcing workers with general cultural levels; (5) KG: Specific KG (SKG or TKG) they use; (6) Links: The storage address of the datasets. The statistical results are shown in Table 3.

| Datasets                    | Domain         | Question type | # Ques. | Q&A source    | KG       | Links                           |
|-----------------------------|----------------|---------------|---------|---------------|----------|---------------------------------|
| Free917 [358]               | General        | Static        | 917     | Expert        | Freebase | <a href="https://">https://</a> |
| WebQuestions [359]          | General        | Static        | 5,810   | Crowdsourcing | Freebase | <a href="https://">https://</a> |
| WebQuestionsSP [360]        | General        | Static        | 4,737   | Crowdsourcing | Freebase | <a href="https://">https://</a> |
| ComplexQuestions [361]      | General        | Static        | 2,100   | Expert        | Freebase | <a href="https://">https://</a> |
| MetaQA/1-hop [362]          | Movie          | Static        | 116,045 | Generate      | Wikidata | <a href="https://">https://</a> |
| MetaQA/2-hop [362]          | Movie          | Static        | 148,724 | Generate      | Wikidata | <a href="https://">https://</a> |
| MetaQA/3-hop [362]          | Movie          | Static        | 142,744 | Generate      | Wikidata | <a href="https://">https://</a> |
| QALD [363]                  | General        | Static        | 806     | Expert        | DBpedia  | <a href="https://">https://</a> |
| LC-QuAD [364]               | General        | Static        | 5,000   | Generate      | DBpedia  | <a href="https://">https://</a> |
| LC-QuAD2.0 [365]            | General        | Static        | 5,000   | Generate      | DBpedia  | <a href="https://">https://</a> |
| TempQuestions [366]         | General        | Temporal      | 1,271   | Expert        | Freebase | <a href="https://">https://</a> |
| TimeQuestions [280]         | General        | Temporal      | 16,181  | Expert        | Wikidata | <a href="https://">https://</a> |
| CRONQUESTIONS [273]         | General        | Temporal      | 410,000 | Expert        | Wikidata | <a href="https://">https://</a> |
| Complex-CRONQUESTIONS [282] | General        | Temporal      | 45,821  | Expert        | Wikidata | <a href="https://">https://</a> |
| MultiTQ [367]               | Social Science | Temporal      | 500,000 | Expert        | ICEWS    | <a href="https://">https://</a> |

Table 3 Dataset statistics of graph-based reasoning.

## 5.2 Table-based reasoning

The task of table-based reasoning mainly refers to table question answering (Table QA), where symbolic knowledge is stored in the structured table.

### 5.2.1 Table question answering

**Task definition:** Given a question and a table, Table QA methods are required to understand the intent of the question via the parametric knowledge bases and find the correct answer from the table. The table QA methods can be divided into: structure-based, table-to-text, instruction fine-tuning, and hybrid reasoning methods.

### 5.2.1.1 *Structure-based methods*

Structure-based methods parse the table structure and utilize the relationships between rows, columns, and cells to find the final answers. This approach has proven effective in extracting structured insights by focusing on the table's inherent organization.

Many methods primarily focus on understanding the semantic association between table headers and data areas. For example, Müller [368] proposes encoding a table into a graph and employing GNNs and pointer networks to select answers and address sequential questions directly from the table. Similarly, TAPAS [290] flattens tables, encodes structure through multiple positional embeddings, and uses pre-training on text-table pairs to predict cell selections and aggregation operators for Table QA. GRAPPA [291] takes a different approach by inducing synchronous context-free grammar to generate synthetic data, combining pre-training on masked language modeling and SQL semantic prediction. This enables GRAPPA to utilize structural knowledge effectively for semantic parsing, converting user inputs into executable programs, and enhancing performance across various datasets.

However, while these methods excel in querying structured data accurately, they face significant limitations when dealing with complex tables, such as nested structures, multi-table setups, or untitled data. They also struggle with flexible questions or generative tasks, highlighting a gap in adaptability. To address these challenges, a few methods have been introduced. For example, TABVER [292] integrates arithmetic reasoning with natural logic reasoning systems, enabling tabular fact-checking tasks to overcome the limitations of symbolic reasoning models and natural logic systems in handling arithmetic operations. Similarly, CARP [293] employs mixed-modal reasoning chains to explicitly model intermediate reasoning steps, improving the interpretability of the model's reasoning process. Despite these advancements, studies reveal that when rows and columns are rearranged to create new examples, the performance of large models declines significantly. This suggests that current approaches to table structure understanding lack robustness and fail to adapt effectively to structural changes [369].

### 5.2.1.2 *Table-to-text methods*

Table-to-text methods first convert tabular data into natural language descriptions. Then, it leverage the natural language descriptions to support the reasoning process. Table-to-text methods is flexible and capable of handling complex queries. However, its performance heavily depends on training quality and demands significant computational resources while offering limited explainability.

To address these challenges, several models and frameworks have been proposed. For instance, OPENT2T [294], an open-source toolkit, facilitates the replication and comparison of existing systems, driving innovation in developing new models. Another example is Table-GPT [295], which proposes a "table-tuning" paradigm to improve language models' performance on table-related tasks. Additionally, methods for summarizing table contents enable users to complete question-answering tasks without needing to browse individual entries in the table [370–372]. Despite these advancements, current research primarily focuses on surface-level achievements, with limited attention to logical reasoning. While existing methods address issues of surface authenticity, they often restate data facts without demonstrating robust reasoning or generalization capabilities. Logical natural language generation [373] aims to bridge this gap by enabling models to generate logically inferred natural language statements from facts in open-domain, structured tables.

### 5.2.1.3 *Instruction fine-tuning methods*

Recently, efforts have been made to enhance LLMs' ability to process table data by developing specialized instruction fine-tuning datasets. Notable among these are TrixInstruct [297] and TableLlama [298], which utilize datasets that cover diverse, realistic tables and related tasks. After fine-tuning on these datasets, LLMs show significant improvements in handling table-based questions. Additionally, ChatQA [299] employs a two-stage instruction fine-tuning strategy, yielding substantial gains in table-related tasks. The first stage involves supervised fine-tuning on diverse instruction datasets, while the second stage, context-enhanced instruction fine-tuning, incorporates table QA and other high-quality QA datasets to further refine the model's conversational QA capabilities in context-specific scenarios.

#### 5.2.1.4 Hybrid reasoning methods

Hybrid reasoning methods combine the above methods with more advanced deep learning technology to process table QA, making it well-suited for multi-step reasoning and complex tasks [374, 375].

Building on this foundation, HRoT [303] introduces retrieval thinking and LLM as a retrieval module, which reconstructs the tables and constructs prompts. In the reasoning stage, it guides the model to retrieve evidence in texts and tables gradually, avoiding the use of irrelevant information and significantly improving the effectiveness of the retrieval process. S3HQA [302] proposes a three-stage framework—comprising retrieval, selector, and reasoner—where LLMs are employed as generative components in the reasoning stage. Expanding on this concept, MMHQA-ICL [304] converts tables and images into text and sends it to the Classifier and Retriever Module for the question type and retrieved documents. Then the Prompt Generator Module builds an LLMs input using the questions and retrieved data. Finally, LLMs give the exact answer. This end-to-end LLM prompt method performs better than the baseline method on the Multimodal QA dataset. While the hybrid reasoning method is effective in solving complex table question answering tasks, it comes with drawbacks such as being complex to implement, requiring high computing resources, and in certain situations, needing manual rule design or model fine-tuning, EXPLORA [305] offers a distinct perspective which can save resources by reducing the number of LLM calls. As a static subset selection method, it uses a scoring function to select examples, bypassing reliance on LLM parameters or outputs.

#### 5.2.2 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to table-based reasoning, including (1) Domain: The domain of knowledge corresponding to the datasets; (2) # Ques.: Question number; (3) Q&A source: The main construction methods of questions and answers. They are mainly divided into three categories: “Generate”, “Expert”, and “Crowdsourcing”. “Generate” refers to the design of programs for automated generation, “Expert” refers to direct crawling from professional websites or carefully designed by domain experts, and “Crowdsourcing” refers to completion by crowdsourcing workers with general cultural levels; (4) Table source: The source of tables; (5) Links: The storage address of the datasets. The statistical results are shown in Table 4.

| Datasets            | Domain  | # Ques. | Q&A source                     | Table source                              | Links                           |
|---------------------|---------|---------|--------------------------------|---|---------------------------------|
| HiTab [376]         | General | 14 K    | statistical reports, Wikipedia | Crowdsourcing                             | <a href="https://">https://</a> |
| FeTaQA [377]        | General | 10 K    | Crowdsourcing                  | Wikipedia                                 | <a href="https://">https://</a> |
| WikiSQL [296]       | General | 24 K    | Expert                         | Wikipedia                                 | <a href="https://">https://</a> |
| TableInstruct [298] | General | 1.24 M  | Expert                         | Wikipedia, statistical scientific reports | <a href="https://">https://</a> |
| FEVEROUS [378]      | General | 87 K    | Expert                         | Wikipedia                                 | <a href="https://">https://</a> |
| TableBench [306]    | General | 0.8 K   | Crowdsourcing                  | existing datasets                         | <a href="https://">https://</a> |
| BanglaTabQA [300]   | General | 19 K    | Generate                       | Wikipedia                                 | <a href="https://">https://</a> |
| ChatRAG Bench [299] | General | 29.2 K  | Expert                         | Internet                                  | <a href="https://">https://</a> |
| KET-QA [307]        | General | 13 K    | Crowdsourcing                  | Wikidata                                  | <a href="https://">https://</a> |
| IM-TQA [79]         | General | 1.2 K   | Crowdsourcing                  | published studies                         | <a href="https://">https://</a> |

Table 4 Dataset statistics of table-based reasoning.

### 5.3 Text-based reasoning

The tasks of text-based reasoning include Machine reading comprehension (MRC), Multi-hop reading comprehension (MHRC), also known as multi-hop question answering), Open-domain question answering (ODQA), and Multi-document question answering (MDQA), where symbolic knowledge is stored in unstructured text.

#### 5.3.1 Machine reading comprehension

**Task definition:** Machine reading comprehension aims to evaluate a machine’s ability to understand language effectively. MRC methods are presented with one or more text passages and are then required to answer questions based on the provided passages [53, 309, 379, 380]. As highlighted by [56, 381], improving MRC performance involves developing several skills, including numerical reasoning, commonsense reasoning, and logical reasoning.

The research on machine reading comprehension has garnered significant interest over the past decade. The MRC tasks have progressed from the initial cloze-style tests [382,383] to span-based answer extraction from passages [384, 385], as well as to multiple-choice [386] and free answering formats [387]. In the early years, rule-based methods [388, 389] focus on designing heuristic algorithms. These algorithms are specifically tailored to the grammar of a language and are used to assist in learning, discovery, or problem-solving. By employing trial-and-error techniques, they aim to find evidence within a given sentence to answer a question. Statistic-based methods [390] involves quantifying occurrences of words and utilizing these numerical representations to infer potential answers. Recently, numerous studies [391, 392] focus on leveraging machine learning methods to extract the features in the questions and passages, which enhance the machine's ability to understand and process text automatically.

With the development of deep learning, various attention-based methods [393–396] are proposed to facilitate interactions between passages and questions. Recently, PLMs have achieved significant success in MRC tasks. The PLMs-based models demonstrate a strong ability to capture contextual and sentence-level language representations, which notably improve the benchmark performance of current MRC systems [53, 56, 309]. In line with this trend, our focus is primarily on PLMs-based MRC methods, which combine symbolic knowledge in text passages and parameter knowledge in PLMs. The PLMs-based MRC methods can be further divided into Extractive MRC and Generative MRC [316]. The Extractive MRC methods try to predict the start and end positions of answers directly from the context, while the Generative MRC methods are devoted to generating answers by reformulating information across the context.

### 5.3.1.1 *Extractive MRC methods*

Recent MRC research predominantly focuses on extractive question answering using encoder-only PLM, which predicts the start and end positions of answers directly from the context. For instance, CTX [308] adopt PLMs to independently obtain paragraph representations conditioned with the current question, previous questions, and previous answers. To extract the answer span, the start and end positions of the current answer are predicted based on the concatenation of the paragraph representations encoded in the previous step.

In this category of methods, PLMs are mainly used as encoders to extract general features from text paragraphs and questions. The focus is on designing downstream models to extract task-oriented features. For instance, SG-Net [309] leverages syntactic guidance in text modeling, achieving substantial performance gains in MRC by introducing explicit syntactic constraints in the attention mechanism. Inspired by how humans solve reading comprehension questions, Retro-Reader [53] integrates two reading and verification strategies stages. First, it uses sketchy reading to quickly grasp the relationship between the passage and the question, forming an initial judgment. Then, it conducts intensive reading to verify the answer and provide the final prediction. Focal Reasoner [56] extracts fact units from raw texts via syntactic processing and constructs a supergraph. Then, it performs reasoning over the supergraph and a logical fact regularization and aggregates the learned representation to decode the correct answer. Extract-Integrate-Compete [54] iteratively selects complementary evidence with a novel query updating mechanism and adaptively distills supportive evidence, followed by a pairwise competition to push models to learn the subtle difference among similar text pieces.

In the methods mentioned above, the system is mainly expected to extract a single answer from the passage for a given question. However, in many scenarios, questions may have multiple answers scattered in the passages, and all the answers should be found to answer the questions completely. For extracting answers with multi-span, TASEBIO [310] transfers MRC to a sequence tagging task, predicting whether each token is part of the answer. MTMSN [311] combines a multi-type answer predictor designed to support various answer types (e.g., span, count, negation, and arithmetic expression) with a multi-span extraction method for dynamically producing one or multiple text spans. SpanQualifier [55] presents a novel span-centric scheme to generate representations for all spans in the context and predicts a qualification threshold. Furthermore, it designs a global loss function to jointly optimize overall spans instead of independently optimizing loss on each individual span, which avoids the influence of label imbalance on training the proposed span-centric scheme.

### 5.3.1.2 *Generative MRC methods*

Recently, significant progress has been made in controllable text generation. Beyond extractive meth-

ods, there is also growing interest in applying generative language models for extractive MRC, which generate answers by reformulating information across the context. For instance, RBG [312] combines a Seq2Seq language model-based generator with a machine reading comprehension module. The reader produces an evidence probability score for each sentence, which will be integrated with the generator for final distribution prediction. KEAG [313] composes a natural answer by exploiting and aggregating evidence from all four information sources available: question, passage, vocabulary, and knowledge. During the process of answer generation, KEAG adaptively determines when to utilize symbolic knowledge and which fact from the knowledge is useful. REAG [314] incorporates an extractive mechanism into a generative model to leverage relevant information to a given question in the contextual passage. Specifically, REAG adds an extraction task on the encoder to obtain the rationale for an answer, which is the most relevant piece of text in an input document to the given question. FiD [315] adopts a simple attention-based inference strategy to extract answer spans from a seq2seq Transformer model without introducing any additional parameters. It then proposes a joint training strategy by combining the normal generative loss and a span extractive loss by enforcing cross-attention to align with answer span positions within the context passages. QASE [316] proposes a novel adaptation of controlled text generation tailored to the specific challenges of MRC, focusing on the precision and relevance of generated answers. Unlike methods that modify the overall generative process through complex architectural alterations or additional learning mechanisms, QASE directly utilizes the question and context to guide inferences.

For multi-span answers, MUSST [317] combines the benefits of span extraction and the simplicity of a multi-span approach to generate free-form answers. It also provides a comprehensive framework for multi-passage generative MRC, which consists of a passage ranker, a multi-span answer annotator, and a question-answering module. CAMRC [318] proposes an answer making-up method from extracted multi-spans learned as highly confident n-gram candidates in the given passage. Unlike the studies that mainly focus on introducing generative mechanisms, SAMSG [319] focuses on handling the writing form of the answer and proposes a novel non-generative decoder to exploit the results from the extractive decoder fully. It learns to score every word in the given passage for how likely they are in the expected answer, then calculates the score of a candidate span from the words' scores.

### 5.3.2 Multi-hop reading comprehension

**Task definition:** Multi-hop reading comprehension methods focus on integrating and reasoning over multiple pieces of evidence to answer complex questions. Unlike single-hop MRC, where questions are typically straightforward, and answers can be derived from one or a few nearby sentences, MHRC involves reasoning chains that traverse multiple sentences or even passages. This requires a deep text understanding and reasoning capability, making it more akin to real-world scenarios.

The key challenge of MHRC lies in its demand for multi-step reasoning, where a model must identify and connect intermediate information to form a coherent reasoning path. This reasoning chain culminates in the extraction of the correct answer, supported by a series of evidence sentences. Therefore, MHRC not only tests a model's ability to find the answer but also its capacity to justify the reasoning process with a clear rationale, presenting evidence as proof of the multi-hop reasoning process. Datasets like HotpotQA [397] have been specifically designed to evaluate such multi-hop reasoning capabilities. They include tasks that expect the model to extract and present evidence sentences, thereby showing a clear reasoning trail. Consequently, MHRC better aligns with real-world scenarios where information is dispersed across long passages or multiple documents, necessitating more comprehensive models than those used for single-hop MRC tasks. In MHRC, the given passages are considered as symbolic knowledge bases, and the parametric knowledge bases (PLMs) are adopted to encode the questions and the passages. In MHRC, methods are primarily divided into two categories: graph-based and graph-free methods [327, 331, 332]. Graph-based methods must construct and reason over a graph structure created from the input data. However, graph-free methods do not rely on such structures and often utilize techniques like self-attention for reasoning.

#### 5.3.2.1 Graph-based MHRC methods

The main idea behind graph-based approaches is to represent the input data, which includes the context and questions, as a graph structure. This involves creating nodes representing entities or pieces of text and edges to denote relationships or co-occurrences between these nodes. The reasoning process in MHRC is then performed through message passing over this graph, which allows the model to simulate

the multi-hop reasoning process as it navigates through various interconnected nodes.

Most current research relies on entity graphs where nodes are formed from the context and question entities. For instance, Entity-GCN [398] compiles scattered information from one or more documents by building an entity graph. In this structure, nodes represent entity mentions, while edges illustrate relationships between these mentions within and across multiple documents. BAG [399] transforms documents into a graph in which nodes are entities and edges are relationships between them. The graph is then imported into graph convolutional networks to learn relation-aware representations of nodes. Furthermore, BAG introduces bi-directional attention between the graph and a query with multi-level features to derive the mutual information for the final prediction. Many studies assume that all contexts are pertinent and ignore the negative impact of irrelevant contexts. To filter out unrelated context, DFGN [400] designs a paragraph-selection module to eliminate unrelated paragraphs. It dynamically builds an entity graph from the question entities to locate relevant supporting entities and text spans. Based on DFGN, DFGN-Dual [401] introduces dual reasoning channels to predict the final answer and supporting facts, respectively, which gain better step-by-step reasoning compared to a single-channel approach. Similarly, SAE [402] incorporates a paragraph-selection step to filter out irrelevant context segments, thereby shrinking the problem space while utilizing sentences as graph nodes.

To further improve the performance, some methods try to emulate the human brain's cognitive processes for multi-hop MRC. For example, inspired by the dual process theory of human [403–406], CogQA [320] builds a cognitive graph in an iterative process by coordinating an implicit extraction module and an explicit reasoning module. The extraction module extracts question-relevant entities to construct the cognitive graph. Then, the reasoning module conducts the reasoning procedure over the graph and collects clues to guide the extraction module in extracting next-hop entities better. DRN [321] designs a query reshaping mechanism that visits a query repeatedly to mimic people's reading habits. It dynamically reasons over an entity graph with graph attention and the query reshaping mechanism to promote its comprehension and reasoning ability.

In addition to the work mentioned above, other approaches design models from different perspectives. For instance, DRL-MHRC [322] proposes an RL-based method capable of learning sequential reasoning across extensive collections of documents to pass a query-aware, fixed-size context subset to existing models for answer extraction. BERT-Para [323] first extracts a discrete reasoning chain over the text, which consists of a series of sentences leading to the answer. It then feeds the extracted chains to a BERT-based QA model to predict the final answer. IP-LQR [324] incorporates phrases in the latent query reformulation to improve the cognitive ability of the proposed method for MHRC.

Some studies try to construct more intricate graphs using multiple node types to encompass the available contextual information in the graph constructions fully. For instance, HDE [325] proposes a heterogeneous document-entity graph, which contains different granularity levels of information, including candidates, documents, and entities in specific document contexts. To aggregate clues from scattered texts across multiple paragraphs, HGN [326] creates a hierarchical graph by constructing nodes on different granularity levels, including questions, paragraphs, sentences, and entities. Furthermore, TA-MHRC [327] uses more helpful information about the context, such as the topic of sentences, the topic of relationships, and the importance and strength of relationships, when filtering paragraphs and constructing the graph. Thus, the proposed graph is a weighted graph with four types of nodes and six types of edges to cover the complete information of the context.

### 5.3.2.2 Graph-free MHRC methods

Compared with the graph-based methods, graph-free methods avoid the explicit construction of graph structures. Instead, they typically rely on more straightforward architectures, possibly leveraging PLMs and self-attention mechanisms to process input data. It is worth noting that C2FReader [328] finds that graph structure can play an important role only when the PLMs are used in a feature-based manner. While the PLMs are used in the fine-tuning approach, the graph structure may not be helpful.

Although graph-free approaches suffer from a performance gap compared to the best graph-based models, numerous methods try to merge the gap by designing powerful mechanisms. DecompRC [329] first decomposes the multi-hop question into several single-hop sub-questions according to a few reasoning types in parallel. Then, DecompRC leverages a single-hop reading comprehension model for every reasoning type to answer each sub-question and combines the answers according to the reasoning type. Finally, DecompRC leverages a decomposition scorer to judge which decomposition is the most suitable

and outputs the answer from that decomposition as the final answer. QUARK [330] scores individual sentences from an input set of paragraphs based on their relevance to the question. Then, it feeds the highest-scoring sentences to a span prediction model to produce an answer to the question. Finally, it scores sentences from the input set of paragraphs again to identify the supporting sentences using the answer. S2G [331] retrieves evidence paragraphs in a coarse-to-fine manner, incorporated with two novel attention mechanisms to restrict the receptive fields of each token according to the nature of each specific task. Inspired by the F1 score, R<sup>3</sup> [332] develops an F1 Smoothing mechanism to calculate the significance of each token within the smooth distribution. Furthermore, it incorporates curriculum learning [407] and devises the linear decay label smoothing algorithm, gradually reducing the smoothing weight and allowing the model to focus on more challenging samples during training. FE2H [333] introduces a document selection module that iteratively performs binary classification tasks to select relevant documents by simply adding a prediction layer on a PLM. Then, it trains the reader module on a single-hop QA dataset and transfers it into the multi-hop QA task inspired by humans' progressive learning process.

### 5.3.3 Open-domain question answering

**Task definition:** Open-domain question answering methods are required to retrieve relevant passages from a large-scale corpus and generate the final answer based on the retrieved passages. The ODQA task is more challenging than MRC and MHRC, which search the support facts within a smaller set of candidate passages. Recently, ODQA has been widely used to test the retrieval augmented generation (RAG) systems [342, 343].

Most ODQA methods follow a retrieve-and-read pipeline [28, 30, 408]. The objective of the retrieval phase is to retrieve evidence-related passages from a large symbolic knowledge corpus, such as Wikipedia<sup>1)</sup>. The retriever can be divided into sparse retrieval and dense retrieval. Sparse retrieval methods rely on word-level matching to link vocabulary with documents. Notable methods include Boolean Retrieval [409], BM25 [410], SPLADE [411], and UniCOIL [412]. Dense retrieval methods capture deep semantic information to comprehend the underlying semantics of documents, thereby enhancing retrieval accuracy. Key examples include DPR [413], ANCE [414], RocketQA [415], E5 [416], DrBoost [417], and SimLM [418]. The goal of the reading phase is comprehension and reasoning, akin to MRC, to derive answers based on the retrieved passages. Generally, existing readers can be categorized into extractive readers and generative readers. Extractive readers predict an answer span from the retrieved passages. Notable methods include REALM [49], Skylinebuilderretro [50], RETRO [51], and BPR [52]. Generative Readers generate answers in natural language using sequence-to-sequence models. Key examples include RAG [66], Fusion-in-Decoder [73], MDR [419], and RALM [420].

Recently, the emergence of LLMs has demonstrated their potential for open-domain question answering [336]. This section mainly investigates how to leverage the LLMs to optimize the retrieve-and-read pipeline. At the retrieval stage, the LLMs can be utilized for query reformulation and Enhanced retrieval. At the reader stage, LLMs can serve as augmented readers.

#### 5.3.3.1 Query reformulation methods

Query reformulation methods focus on refining input questions to convey user intent more accurately. For instance, EAR [334] first applies a query expansion model to generate a diverse set of queries and then uses a query reranker to select the ones that could lead to better retrieval results. QPaug [335] decomposes the original questions into multiple-step sub-questions. By augmenting the original question with detailed sub-questions and planning, QPaug can make the query more specific on what needs to be retrieved, improving the retrieval performance. Chain-of-Rewrite [336] finds that current methods face challenges stemming from term mismatch and limited interaction between information retrieval systems and LLMs. Hence, it leverages the guidance and feedback gained from the analysis to provide faithful and consistent extensions for effective question answering. Specifically, CLASS [80] employs LLMs for query transformation via in-context learning in Cross-lingual ODQA tasks.

#### 5.3.3.2 Enhanced retrieval methods

Enhanced retrieval methods adopt LLMs as knowledge sources to provide relevant contextual documents, thereby increasing the likelihood of uncovering the correct answer. This method category is

<sup>1)</sup><https://www.wikipedia.org>

special because they directly use LLMs to generate evidence-related passages, replacing the retrieval process. Although they do not directly utilize the knowledge from a symbolic knowledge base, we still introduce it due to its advanced features. For instance, HintQA [337] produces multiple hints for each question. Then, it substitutes the retrieved passages and generated contexts with the generated hints. GenRead [338] prompts an LLM to generate contextual documents based on a given question and then reads the generated documents to produce the final answer. Self-Prompting [339] prompts LLMs step by step to generate multiple pseudo QA pairs with background passages and explanations entirely from scratch. These generated elements are then utilized for in-context learning. MedGENIE [340] prompts a medical LLM to furnish multi-view background contexts for a given question. Then, it designs two readers for prompting LLMs and fine-tuning SLMs, respectively.

### 5.3.3.3 Augmented reader methods

At the reader stage, LLMs can serve as augmented readers, effectively minimizing distractions from irrelevant documents and improving the quality of the context. To overcome the challenges posed by irrelevant retrieved documents and overconfident scores, DAS [341] propose a negation-based instruction to allow LLMs to abstain from answering. Then, it designs a score adjustment strategy to adjust the answer scores by reflecting the query generation score as the relevance between the given query-document pairs. Considering that LLMs cannot precisely assess the relevance of retrieved documents, thus likely leading to misleading or even incorrect utilization of external knowledge, REAR [342] incorporates an assessment module that precisely assesses the relevance of retrieved documents and proposes an improved training method based on bi-granularity relevance fusion and noise-resistant training. RE-RAG [343] introduces a relevance estimator that not only provides relative relevance between contexts as previous rerankers did but also provides confidence, which can be used to classify whether the given context is helpful in answering the given question. FastFiD [344] performs sentence selection post the output of the reader's encoder and maintains only the essential sentences as references for the reader's decoder, thereby significantly reducing the inference time for each query. Considering that the retrieved context may contain noise and irrelevant information and augmenting noisy context can potentially distract LLMs, TA-ARE [345] dynamically determines retrieval necessity and relies only on LLMs' parametric knowledge when deemed unnecessary.

### 5.3.4 Multi-document question answering

**Task definition:** Multi-document question answering methods aims to find the supporting facts from multiple entire documents. MDQA demands a thorough understanding of the logical associations among the contents and structures of documents.

Although some methods also claim to perform document-based QA, they typically focus on paragraphs with key information, not the entire document. An entire document is usually much longer than a paragraph and contains more distracting information. MDQA requires methods to identify support facts from the entire document, which is challenging. First, an entire document can be very lengthy, and supporting facts may comprise only a tiny part. Moreover, the text within a document is often on a single topic, making different passages highly related and difficult to distinguish.

Recently, a few excellent methods have been proposed for MDQA. KGP [346] formulates the proper context in prompting LLMs for MD-QA, which consists of a graph construction module and a graph traversal module. For graph construction, KGP creates a KG over multiple documents with nodes symbolizing passages or document structures (e.g., pages/tables) and edges denoting the semantic/lexical similarity between passages or document structural relations. For graph traversal, KGP designs an LLM-based graph traversal agent that navigates across nodes and gathers supporting passages to assist LLMs in MD-QA. Considering that some questions often require synthesizing information from multiple frequently unrelated documents, CuriousLLM [347] fine-tunes a decoder-only LLM to emulate the curious nature of a human researcher to generate follow-up questions based on both the initial user query and passages retrieved in previous steps. These questions serve as a guide to identify the most relevant neighboring passages for the subsequent hops in the search process.

### 5.3.5 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to graph-based reasoning, including (1) Domain: the domain of knowledge corresponding to the datasets; (2) # Ques.: Question number; (3) # Pas.: Passage number; (4) Q&A source: The main construction methods of questions and answers. They are mainly divided into three categories: “Generate”, “Expert”, and “Crowdsourcing”. “Generate” refers to the design of programs for automated generation, “Expert” refers to direct crawling from professional websites or carefully designed by domain experts, and “Crowdsourcing” refers to completion by crowdsourcing workers with general cultural levels; (5) Passage source: The source of passages; (6) Links: The storage address of the datasets. The statistical results are shown in Table 5.

| Datasets                | Domain  | # Ques. | # Pas. | Q&A source    | Passages source            | Links                           |
|-------------------------|---------|---------|--------|---------------|----------------------------|---------------------------------|
| CNN/DailyMail [383]     | News    | 1.38 M  | 312 K  | Generate      | CNN and DailyMail websites | <a href="https://">https://</a> |
| NewsQA [421]            | News    | 120K    | 12.7 K | Crowdsourcing | CNN websites               | <a href="https://">https://</a> |
| PeopleDaily/CFT [421]   | News    | 880 K   | 60K    | Generate      | People Daily websites      | <a href="https://">https://</a> |
| TriviaQA [385]          | News    | 95.9K   | 663 K  | Crowdsourcing | Bing Search                | <a href="https://">https://</a> |
| RACE [386]              | Science | 97.6 K  | 28 K   | Expert        | English Exam               | <a href="https://">https://</a> |
| ARC [422]               | Science | 7,787   | 14 M   | Expert        | Science Exam               | <a href="https://">https://</a> |
| SQuAD1.1 [384]          | General | 107.8 K | 536    | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |
| SQuAD2.0 [423]          | General | 150 K   | 536    | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |
| WikiQA [424]            | General | 3,047   | 29.3 K | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |
| SearchQA [425]          | General | 140 K   | 6.9 M  | Crowdsourcing | Google Search              | <a href="https://">https://</a> |
| HotpotQA [426]          | General | 113 K   | -      | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |
| Natural Questions [427] | General | 3.09 M  | 323 K  | Crowdsourcing | Google Search              | <a href="https://">https://</a> |
| 2WikiMultiHopQA [428]   | General | 192.6 K | -      | Crowdsourcing | Wikipedia and Wikidata     | <a href="https://">https://</a> |
| IIRC [429]              | General | 13 K    | -      | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |
| FanOutQA [430]          | General | 8,339   | -      | Crowdsourcing | Wikipedia                  | <a href="https://">https://</a> |

Table 5 Dataset statistics of text-based reasoning.

## 5.4 Heterogeneous reasoning

Graph-based reasoning, table-based reasoning, and text-based reasoning have all been individually studied extensively. However, reasoning based on two or more heterogeneous symbolic knowledge bases, known as heterogeneous question answering (Heterogeneous QA), is under-studied [353]. Exploring how to explore the knowledge from multiple heterogeneous symbolic knowledge bases fully is extremely important for enhancing the practicality of reasoning methods.

### 5.4.1 Heterogeneous question answering

**Task definition:** Heterogeneous question answering methods aim to find the evidence from heterogeneous knowledge bases to answer a knowledge-intensive question.

Some methods investigate how to leverage symbolic knowledge from different sources, including those on closed domain [302, 431–434] and open domain [435–438], but very limited existing work experiments on graph, table, and text, simultaneously. To promote relevant research, CONVMIX [350] and COMP-MIX [439] collect the heterogeneous QA datasets that require knowledge from all three heterogeneous sources. A simple solution for handling heterogeneous QA is to assemble several specialized systems. In this approach, the input question is dispatched to multiple sub-systems, and one of them is chosen to provide the final answer. Although this method can leverage state-of-the-art models optimized for various information sources, it significantly increases the complexity of the entire system. Additionally, it poses challenges in addressing questions that require reasoning across multiple sources of information [348]. Hence, constructing an integrated system compatible with multiple heterogeneous symbolic knowledge bases is essential and promising. Current methods with integrated systems can be divided into structured-unified and human-imitated methods.

#### 5.4.1.1 Structure-unified methods

The structured-unified methods convert multiple heterogeneous bases into one type. The first type of structured-unified method converts different structures to unstructured text, and the second one converts

different structures to structured graphs. In the first type of method, UniK-QA [348] flatten the lists, tables, and KGs to text using simple heuristics methods. Then, it adopts a text-based QA method as the solution to make full use of the powerful PLMs. UDT-QA [349] unifies both representation and model for ODQA over structured data and unstructured text. The key idea is to augment the retriever with a data-to-text verbalizer for accessing heterogeneous knowledge bases, i.e., KGs from WikiData, tables and texts from Wikipedia. Convinse [350] learns an explicit and structured representation of an incoming question and its conversational context. It harnesses this frame-like representation to uniformly capture relevant evidence from KB, text, and tables. Finally, it adopts a fusion-in-decoder model to generate the answer.

In the second type of method, TrustUQA [351] designs a condition graph to unify tables and KGs and uses an LLM and demonstration-based two-level method for reasoning on condition graph. Explaignn [352] constructs a heterogeneous graph from entities and evidence snippets retrieved from a KG, a text corpus, web tables, and infoboxes. This large graph is then iteratively reduced via GNNs incorporating question-level attention until the best answers and explanations are distilled out. The former gives up the advantage of using formal query languages on structured data, which can support operations such as ranking and averaging. The latter gives up the advantage of the expressiveness and versatility of free-text knowledge representation. As [353] points out, the first type of method sacrifices the benefits of using formal query languages on structured data, which can support operations like ranking and averaging. The second type of method relinquishes the expressiveness and versatility offered by free-text knowledge representation.

#### 5.4.1.2 Human-imitated methods

The human-imitated methods integrate reasoning steps over heterogeneous knowledge bases by mimicking how humans find responses to questions, which break down QA solution processes as tool calls and thoughts. For instance, HumanIQ [81] proposes a human-like approach that teaches LLMs to gather heterogeneous information by imitating how humans use retrieval tools. During the preparation stage, the method is required to identify suitable tools and solution processes using those tools. Then, it leverages an LLM to replicate the solution processes at the inference stage. Similarly, SPAGHETTI [353] obtain evidence from heterogeneous sources in parallel, including structured KG, plain text, linearized tables, infoboxes, and LLM-generated claims that are verified, and gather those evidence to generate the final answer using a few-shot LLM.

#### 5.4.2 Datasets

In this section, we have compiled statistics on some commonly-used datasets related to heterogeneous reasoning, including (1) Domain: the domain of knowledge corresponding to the datasets; (2) # Ques.: Question number; (3) Q&A source: The main construction methods of questions and answers. They are mainly divided into three categories: “Generate”, “Expert”, and “Crowdsourcing”. “Generate” refers to the design of programs for automated generation, “Expert” refers to direct crawling from professional websites or carefully designed by domain experts, and “Crowdsourcing” refers to completion by crowdsourcing workers with general cultural levels; (4) KG: Whether they use KG as knowledge bases; (5) KG size: the number of triplets in KG used; (6) Text: Whether they use Text as knowledge bases; (7) # Pas.: the number of passages; (8) Table: Whether they use Table as knowledge bases; (8) # Table: The number of tables; (9) OR: Whether they support open retrieval; (10) HQ: Whether the questions are constructed by human; (11) OD: Whether the answers could be found in open domain; (12) Links: The storage address of the datasets. The statistical results are shown in Table 6.

## 6 Future directions

To enhance the feasibility of reasoning systems in real-world applications, we may need to focus on three key aspects: performance, cost, and security. We have provided some insights into future directions based on these aspects to foster the development of reasoning systems.

| Datasets           | Domain  | # Ques. | Q&A source    | KG | KG size | Text | # Pas. | Table | # Table | OR | HQ | OD | Links                           |
|--------------------|---------|---------|---------------|----|---------|------|--------|-------|---------|----|----|----|---------------------------------|
| WIKIMOVIES [431]   | Movie   | 100 K   | Generate      | ✓  | -       | ✓    | 17 K   | ✗     | -       | ✓  | ✗  | ✗  | <a href="https://">https://</a> |
| HYBRIDQA [432]     | General | 70 K    | Crowdsourcing | ✗  | -       | ✓    | 293 K  | ✓     | 13 K    | ✗  | ✓  | ✓  | <a href="https://">https://</a> |
| MULTIMODALQA [440] | General | 30 K    | Generate      | ✗  | -       | ✓    | 218 K  | ✓     | 10 K    | ✓  | ✗  | ✓  | <a href="https://">https://</a> |
| OTT-QA [435]       | General | 45 K    | Crowdsourcing | ✗  | -       | ✓    | -      | ✓     | -       | ✓  | ✓  | ✓  | <a href="https://">https://</a> |
| MANYMODALQA [441]  | General | 10 K    | Crowdsourcing | ✗  | -       | ✓    | 3,789  | ✓     | 528     | ✗  | ✓  | ✓  | <a href="https://">https://</a> |
| TAT-QA [442]       | General | 17 K    | Crowdsourcing | ✗  | -       | ✓    | 3,902  | ✓     | 7,431   | ✗  | ✓  | ✗  | <a href="https://">https://</a> |
| FINQA [443]        | Finance | 8,281   | Crowdsourcing | ✗  | -       | ✓    | -      | ✓     | -       | ✗  | ✓  | ✗  | <a href="https://">https://</a> |
| HETPQA [444]       | Product | 6,000   | Crowdsourcing | ✗  | -       | ✓    | -      | ✓     | -       | ✗  | ✓  | ✗  | <a href="https://">https://</a> |
| COMPmix [439]      | General | 9,410   | Crowdsourcing | ✓  | -       | ✓    | -      | ✓     | -       | ✓  | ✓  | ✓  | <a href="https://">https://</a> |

**Table 6** Dataset statistics of heterogeneous reasoning.

## 6.1 Improving OOD generalization and robustness of reasoning

Despite the good performance and generalization of LLMs in various general reasoning tasks, such as mathematical reasoning and commonsense reasoning, in some specific domains like healthcare and biology, we still rely on domain-specific data to construct the required reasoning systems based on LLMs. This includes introducing domain-specific pre-training corpora for continued pre-training [445], introducing post-training data for instruction fine-tuning or alignment fine-tuning [446], or incorporating domain-specific knowledge bases for retrieval-augmented reasoning. This poses a hidden risk: due to the limited availability of domain-specific data, these reasoning systems may perform well on seen data but demonstrate poor generalization and instability on unseen out-of-distribution (OOD) instances [447–449]. Therefore, exploring and enhancing the generalization and robustness of these domain-specific reasoning systems is an important research direction. The following lists some potential research directions:

- **Scalable reasoning training data construction:** Scalable data construction methods based on limited in-domain data may help reasoning systems generalize to more reasoning examples since it can expand the distribution encountered during the training process [450, 451]. In this direction, ensuring the quality and diversity of the expanded data will be a core research issue.
- **Rule-guided reasoning:** One of the advantages of symbolic reasoning [452] is that it is not limited by the finite distribution of training data, which may help improve the generalization and robustness of reasoning systems. Specifically, future research could explore how to derive executable reasoning rules from existing in-domain data and how to apply these reasoning rules during the inference phase for symbolic reasoning, thereby enhancing its reliability.

## 6.2 Cost-efficient reasoning

Existing strategies to enhance reasoning system performance, such as chain-of-thought, self-consistency, and feedback-enhanced reasoning, often become inefficient due to the need to generate more tokens. In practical applications, we desire reasoning systems that not only demonstrate good performance but also have minimal reasoning time and cost. Hence, future research could focus on proposing cost-efficient reasoning strategies while improving or maintaining reasoning system performance. To address this issue, future research can attempt the following:

- **Incorporating symbolic reasoning strategies:** Although rule-based symbolic systems [452, 453] and probabilistic statistical models are less effective compared to complex neural systems like LLMs, they can handle simple reasoning problems or some simple reasoning steps in complex reasoning problems. Exploring how to integrate symbolic systems, statistical models, and LLMs to collaboratively reason may help achieve cost-efficient reasoning while maintaining powerful performance.
- **Efficiency-adaptive reasoning:** For humans, the reasoning cost required for simple problems differs from that for more complex problems. How to adaptively engage in fast-thinking reasoning for simpler problems and slow-thinking reasoning for more difficult ones is a promising approach to achieving cost-efficient reasoning [454, 455].

### 6.3 Ensuring the safety of reasoning

Ensuring the safety of reasoning involves two aspects. First, ensuring that the reasoning processes and results do not contain harmful or potentially dangerous contents. Second, ensuring that private information from local symbolic knowledge bases is not leaked to cloud-based LLMs.

#### 6.3.1 Preventing toxicity while reasoning

Reasoning is a knowledge-intensive task where we infer new knowledge from existing knowledge. We want this new knowledge to be harmless and not cause negative impacts on society or individuals. However, current toxicity detection or detoxification work mainly focuses on hate or biased speech in general texts [456–460], not on such knowledge-intensive reasoning tasks. Compared to general texts, texts in reasoning processes and results contain more specialized knowledge, such as chemistry, biology, physics, and mathematics. For example, designing molecular formulas for drug creation can be harmful but hard to detect based on text semantics alone. Therefore, conducting toxicity detection or detoxification for such knowledge-intensive reasoning tasks is a challenge and a significant concern. The following is a potential research direction:

- **Incorporating domain-specific expertise:** To ensure the security of reasoning processes and results, augmenting traditional toxicity detection approaches with domain-specific expertise may be necessary. This involves integrating interdisciplinary insights from fields like chemistry, biology, and physics with AI safety frameworks to identify potential harm beyond surface-level text semantics.

#### 6.3.2 Protecting data privacy while reasoning

Recently, an increasing number of applications have integrated their local symbolic knowledge bases with third-party LLMs for retrieval-augmented generation [461], which enhances the accuracy and credibility of the generation for domain-specific reasoning. However, it poses potential privacy leakage risks. Taking KGQA as an example, the local KG contains many triplets involving private data, especially in entities. Meanwhile, many high-performance LLMs in the cloud operate in a black-box manner through API calls. Current methods, particularly IR-based methods, require these triplets to be transmitted indiscriminately to the LLM, even though most entities are unnecessary for the reasoning process. Therefore, protecting data privacy while reasoning in a de-identification scenario by combining the local knowledge base with third-party LLMs is a challenge and an important focus. Here is a potential research direction:

- **Reasoning in scenarios where most entity names are anonymized:** To ensure that private information in the local knowledge base is not exposed to third-party LLM during the reasoning process, it may be necessary to anonymize the specific names of entities in the local knowledge base, such as by replacing them with entity IDs. During the reasoning process, LLM would have to rely solely on the types of entities and their relations, while the semantics of the entities and the rich background knowledge stored in the LLM would no longer be available. This involves the application of traditional privacy computation methods and fully utilizing the LLM's logical reasoning capabilities.

## 7 Conclusion

In this paper, we provide a comprehensive survey on reasoning methods with a specific focus on the usage of knowledge bases, addressing a gap in existing literature. By categorizing knowledge bases into symbolic and parametric types, we offer a novel perspective on how reasoning can be enhanced when leveraging different formats of stored information. Symbolic knowledge bases, such as KGs and tables, offer explicit and human-readable knowledge, while parametric knowledge bases encode knowledge implicitly within parameters, such as large language models. Then, we investigate how these knowledge bases, individually and in combination, support reasoning processes. Additionally, this survey proposes some potential future directions in reasoning research. By providing this comprehensive overview, we hope to inspire further exploration and advancements in the field, ultimately contributing to developing artificial intelligence systems with more robust reasoning capabilities.

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